CSAE WPS/2008-15

Some Child Cost Estimates for South Africa

Alex Sienaert*

May 2008

Abstract

The heterogeneous demographic composition of South African households means that the way that household income or expenditure is converted into an individual-level welfare measure is likely to matter. This paper examines the monetary and time costs of the most common economic dependents in households: children. The monetary costs of children are estimated at about half those of an adult. Time costs are substantial, and borne almost exclusively by women. Estimates that incorporate time costs suggest that children's "full costs" are about twice monetary costs alone; with household resources fixed, the average, combined expenditure and time impact of children is very similar to adding an equivalent number of adults.

Keywords: Household Demand, Time Allocation and Labor Supply, Child Care

JEL Classifications: J13, J22, R22

*DPhil Candidate, Department of Economics and Oriel College, Oxford University. I thank (without implicating) Margaret Stevens for invaluable advice. Preliminary, comments welcome: alexis.sienaert@economics.ox.ac.uk.

1 Introduction

1.1 Question and Motivation

Households come in all shapes and sizes. This complicates both static and dynamic welfare comparisons, notably poverty and inequality estimates. Such estimates inevitably embed assumptions about how to account appropriately for differences in comparison units, but these are often implicit. For example, it is common to convert total household expenditure into an individual welfare measure by dividing by total household size, yielding "per capita" expenditure. This assumes that expenditure is apportioned equally, and that a unit of expenditure buys a fixed amount of welfare. Both these assumptions are questionable: intrahousehold inequalities may be substantial, it seems likely (on physiological grounds) that children benefit more from a rand of consumption than adults, and larger households may reap consumption scale economies. If the last two are true, per capita measures understate welfare in households with children, and larger households (Nelson 1993). At the other extreme, we might simply assign household aggregates to all household members. But, with total resources fixed, people in larger households must be worse off (except in the implausible case where pure public goods account for all consumption). An alternative is to specify an "equivalence scale" – an index that standardises different household types by converting them into adult equivalents. The OECD scale, for example, assigns adult equivalences to the first adult, subsequent adults, and children, of 1, 0.7 and 0.5, respectively. The square root scale performs the eponymous operation on household size (OECD 2005).

The sensitivity of estimates to the choice of standardisation is an empirical matter, but will clearly depend on the degree of heterogeneity along the dimensions of interest (say, race or income). In South Africa, where households are extremely heterogeneous (see Amoateng, Heaton and Kalule-Sabiti (2007)), we might therefore expect this issue to have received considerable attention. With a few exceptions, this is not the case. In fact, the applied labour and poverty literature based on South African household surveys seems to have converged with little comment on either per capita adjustment, or the formula:[1]

$$\text{Adult equivalents} = \left(\text{adults} + 0.5 \times \text{children}\right)^{0.9} \tag{1}$$

This scaling assumes that child wants are half as costly as adults', and embeds weak economies of scale ($s = 0.9$) through the exponent ($0 \leq s \leq 1$). Thus, members of a two-adult, two-child household with total income of 1000 rand enjoy "per adult equivalent" income of 372 rand, compared to 250 rand per capita. While it appears reasonable, this measure is essentially arbitrary. According to Leibbrandt and Woolard (1999), "these values were suggested by Angus Deaton in a lecture given in South Africa in 1993, but were simply suggested as plausible values for the purposes of explaining the principle of the equivalence scale" (p14).

This paper provides some economic estimates of the costs of children in South Africa, as a starting point for addressing this methodological lacuna. There are several reasons for the focus

[1] Articles in which this formula is used include May, Carter and Posel (1995), Posel (1997), Leibbrandt and Woolard (2001), and Klasen and Woolard (2005). Leibbrandt and Woolard (2006) provide a discussion and Engel-method based scale economy estimates, and demonstrate that some important poverty indicators are robust to plausible scale choices.

on children.

First, unlike in many other developing countries, subsistence agriculture is relatively unimportant in South Africa. Livelihoods are sustained mainly by the market labour supply of household residents, private transfers from non-residents, and government grants. In household survey data, therefore, we typically observe not only expenditure, but also individually-attributable income. While we need ultimately to understand intrahousehold distribution to infer individual welfare, it is possible to obtain at least a first impression of individual welfare merely by examining individual-level income data, which is impossible when subsistence production dominates. This tells us nothing, however, about the welfare of zero-income dependents. Since the most numerous dependents are children, relating total household resources to child welfare is the priority for making sensible household composition adjustments to welfare measures in South Africa.

Second, in addition to their instrumental value, child cost estimates have other important uses. There is abundant evidence that children have major impacts on economically-relevant behaviour. Economists have paid relatively little attention to this in South Africa, however, and doing so may shed light on household decision-making and resource allocation dynamics more generally. From a policy perspective, the most significant extension of the social welfare net in recent years has been the child support grant, and economic child cost estimates provide benchmarks for its relative generosity.

Finally, estimating child costs is a more tractable problem than estimating general adult equivalence scales. The venerable "Engel method" for identifying consumption scale economies is discredited (see Deaton (1997), chapter 4), and promising related methods yield nonsensical results, including with South African data (Deaton and Paxson 1998). This is an active research area, and other, theoretically sophisticated approaches exist (fully-articulated demand systems based on intrahousehold resource allocation models). But their data requirements place them beyond the ambit of applied work for South Africa at present.[2]

The aim, then, is to identify the cost of children, as an input to an equivalence scale system. The cost of a child is defined as its impact on adult material welfare, all else equal. This determines the hypothetical compensation for child costs from which equivalence scales can be derived. The notion of child costs, and this definition in particular, raises a host of conceptual issues, many related to broader questions about welfare comparisons, equivalence scales and endogenous fertility. In this paper, I simply treat children as exogenous, and assume both that adult welfare is a reasonable proxy for child welfare, and that "situation comparisons" (Pollak 1991) between households with varying numbers of children are sensible. Pollak (1991), Browning (1992) and Nelson (1993) provide discussions of these issues, some of which are revisited in the conclusion.

1.2 Approach

Three data sets from Statistics South Africa are employed: the Income and Expenditure (IES), September Labour Force (LFS), and Time Use (TUS) surveys, all from the year 2000. Data preparation and methodological choices are described in appendix C. The IES and LFS (but not

[2]For an overview of equivalence scale theory, see chapters 7 and 8 of Deaton and Muellbauer (1980), and references therein. Nelson (1993) is a superb, critical review with an emphasis on policy. Attempts to estimate general equivalence scales for South Africa include Yatchew, Sun and Deri (2003) and examples in Yatchew (2003).

the TUS) survey the same households, and so can be matched to provide a detailed view of household residents' labour status, and income and spending. The three nationally-representative surveys have unusually common sample supports (across space and time), providing an opportunity to consider child cost estimates based on different kinds of data with a low risk of spurious interpretations arising from transitory macro effects or other idiosyncracies.

Child costs are first estimated by the well-known Rothbarth method (Rothbarth 1943), based on IES expenditure data (section 2). This provides estimates of the monetary costs of children. Section 3 examines the effects of children on adult time allocations using the TUS, beginning with an explanation of the concept of the "full" (time-inclusive) costs of children, and their likely underestimation by the Rothbarth method. Section 4 provides estimates of time-augmented adult equivalence scales. Since this involves a number of imputations, these are necessarily tentative. Section 5 concludes. The role of child ages, and possible differences by child gender, are examined in appendix A, and a robustness check conducted in appendix B.

Throughout, children are defined as household residents aged 0-14. The upper bound of 14 is a common child age cutoff in the child costs and welfare evaluation literature, and is appropriate for South Africa since 15 is legal school-leaving age.

2 Rothbarth Method Child Cost Estimates

2.1 Method

Imagine a good which tracks welfare closely; better-off people almost certainly consume more of it. Consumption of the good in fact increases monotonically and smoothly with income or expenditure. Further, the only effect of children on demand for the good is to reduce the resources available for its purchase. The Rothbarth method of child cost estimation is premised on the existence of – and ability to observe – such a good, or group of goods. The cost of children can then be determined by evaluating the compensation required to hold the goods' consumption constant as the number of children increases, all else equal.

In addition to the conceptual problems already alluded to, there are a number of practical problems with this approach, which boil down to the difficulty of finding one or more goods satisfying all the above criteria. Conventional choices include alcohol and tobacco, adult clothing and footwear, and entertainment (such as meals out). The Rothbarth method then deems households to be equally well off if their constituent adults consume, say, the same quantity of brandy and cigars (Browning 1992). It is by no means clear that preferences are homogeneous enough to make this plausible. In addition, we need the elasticity of substitution with respect to children to be negligibly low (while, on the contrary, it is not hard to imagine beleaguered parents taking up smoking)[3], and demand to be income-elastic enough to allow identification using income or expenditure variation.

South Africa should be a relatively good candidate for the Rothbarth method in at least this last respect. If too many households are in extreme poverty, income increases are likely to be spent entirely on food, confounding the method (Deaton 1997). But in South Africa, enough poor households are likely to be far enough away from absolute subsistence to yield a positive income elasticity over most of the expenditure distribution.

[3]This example is less flippant than it might seem: see Atkinson, Stern and Gomulka (1981).

For reviews, implementations, and cautious defenses of the Rothbarth method as providing a useful guide to likely child costs, see Deaton and Muellbauer (1986), Gronau (1991), Tsakloglou (1991) and Deaton (1997), chapter 4.

2.2 Implementation

2.2.1 Engel Curve and Equivalence Scale Derivation

Based on IES data availability, total expenditures on alcohol and tobacco products, and adult clothing and footwear, are selected as the composite adult good. Figure 1 shows that adult goods spending trends upwards with total expenditure (as we require), but also illustrates the material number of zero values throughout the expenditure range. 60% of households spend nothing on alcohol and tobacco, 32% nothing on adult apparel, and 21% nothing on either.

Figure 2 demonstrates the empirical regularity at the heart of the Rothbarth method, displaying local linear regressions of adult good expenditure against the natural log of total expenditure, in two-adult households with varying numbers of children. We see that adult goods spending rises non-linearly with log total expenditure, but that at given total expenditure, adult good expenditure is lower with more children. Over the bulk of the expenditure distribution (where these nonparametric estimates have reasonable precision), this relationship looks quite well-behaved. However, it does appear that the shapes of the 3- and 4-child household curves differ from those of 0-2 child households. Any such associations between demographic parameters and slopes – rather than simply intercepts – of adult good Engel curves complicate equivalence scale estimation.[4]

Based on characterisations such as that of figure 2, the data suggest Engel curves with considerable convexity in the natural log of expenditure over most of their ranges. A quadratic log expenditure term is thus likely to provide a better fit than a linear specification, and represents the best compromise in the trade-off between a precise, and complex, parametric specification of functional form, and straightforward extraction of equivalence scale estimates (noting that, for any practical implementation, these must average over considerable variation).[5] This suggests a modification of the well-known Prais-Houthakker Engel curve (Prais and Houthakker 1955), with Rothbarth regressions taking the form:

$$A = \alpha + \beta_1 \ln x + \beta_2 (\ln x)^2 + \delta \mathbf{D} + \theta \mathbf{Z} + \epsilon \tag{2}$$

where A is adult goods spending, x total expenditure, $\mathbf{D}$ is a vector of household composition controls (including child indicators), $\mathbf{Z}$ is a vector of taste shifters thought to be orthogonal to other correlates and influencing adult goods demand, and ϵ is a random error term. Compensation for reduced adult good consumption due to a difference in demographic composition can be calculated as the extra expenditure predicted to neutralise the demographic effect. This requires that predicted adult goods expenditure ($\hat{A}$) in a household of type i is equal to that of a reference household of type 0. That is, with subscripts denoting household demographic type and hats,

[4] Technically, they violate the shape invariance Engel curve criterion. In this paper, Engel curves are defined broadly, as demand functions of household resources with prices fixed (Lewbel 2008).

[5] See Banks, Blundell and Lewbel (1997) for empirical evidence from the UK, and theory, in support of this functional form.

estimates:

$$\hat{A}_0 = \hat{\alpha} + \hat{\beta}_1 \ln x_i + \hat{\beta}_2 (\ln x_i)^2 + \hat{\delta}\mathbf{D}_i + \hat{\theta}\mathbf{Z}_i \tag{3}$$

When $\beta_2 = 0$ (i.e. adult good spending is linear in log expenditure), equation 3 yields:

$$\frac{x_i}{x_0} = \exp\left(\frac{\hat{\delta}(\mathbf{D}_0 - \mathbf{D}_i) + \hat{\theta}(\mathbf{Z}_0 - \mathbf{Z}_i)}{\hat{\beta}_1}\right) \tag{4}$$

which we define as the equivalence scale for household type i. In the quadratic case at hand:

$$\frac{x_i}{x_0} = \frac{1}{x_0}\exp\left(\frac{-\hat{\beta}_1 \pm \sqrt{\hat{\beta}_1^{\,2} + 4\hat{\beta}_2(\hat{A}_0 - \hat{\delta}\mathbf{D}_i - \hat{\theta}\mathbf{Z}_i)}}{2\hat{\beta}_2}\right) \tag{5}$$

Equivalence scales thus vary with expenditure (are base-dependent), which is expected since the expenditure elasticity of adult goods demand in the quadratic case is non-constant.

2.3 Regression Specification

Severe misspecification of the adult goods Engel curve poses a potential threat to inference. Consequently, results from specification 2 are compared with those from its more classical form, in which β_2 is restricted to zero and adult goods spending is linear in the natural log of expenditure. While *ad hoc*, a linear specification is the most basic counterpoint to the roughly quadratic form suggested by the data, and yields an interesting comparison between child costs assumed to be invariant to expenditure, and those allowed to vary by expenditure.

The disproportionate density mass at zero adult goods expenditure violates the assumption of a normally-distributed dependent variable which underpins OLS estimation. In general, this leads to attenuated partial correlation estimates. This is of direct concern in the present case, since we aim to identify child costs using the negative association between the presence of children and adult goods expenditure. The problem is addressed by applying a standard Tobit model:

$$A = \begin{cases} A^\star & \text{if } A^\star > 0 \\ 0 & \text{otherwise} \end{cases}$$
$$\text{and } A^\star \sim N(\mathbf{X}\beta, \sigma^2)$$

That is, we assume that there is a normally distributed latent variable $A^\star$, with mean $\mathbf{X}\beta$ ($\mathbf{X}$ all regressors described above, and β the conformable coefficient vector) and variance σ^2, representing desired adult goods expenditure. $A^\star$ is observed as 0 when weakly negative, and A when positive. The resultant maximum likelihood function, from which marginal effect estimates are obtained, models the contribution of covariates as determining the probability of A being positive, and the conditional value of $A > 0$, jointly. Variables are assumed to have the same impact on the probability of positive adult goods spending, and the amount spent conditional on positive spending. While clearly restrictive, this is not entirely implausible.

Violations of the normality assumption compromise not only the efficiency, but also the consistency of Tobit estimates. This may be a concern for the case at hand, since we might expect the dispersion of adult goods spending (and hence estimated Engel curve errors) to increase with total expenditure. Appendix B conducts a robustness check.[6]

Households vary not only by the number of children, but also by other demographic characteristics. Since equivalence scales are calculated for households that are identical to a reference household in all respects but one (children), household size and composition must be evaluated explicitly. However, household demography varies in conjunction with the number of children, so it is not clear that we can safely consider demographic controls to be orthogonal to children or, for that matter, to expenditure. For example, more children are associated with the presence of more women (see table 1), who in turn are correlated with lower expenditure (and, it might be expected, weaker preferences for adult goods). The challenge is to balance the risk of collinearity between household make-up variables destabilising the crucial expenditure and child coefficient estimates, and omitted variable bias in their absence.

This motivates two, distinct paramaterisations of the role of demographic composition ($\mathbf{D}$) on adult goods spending. First, "restricted" regressions are conducted on the sub-sample of households containing two adults, with $\delta\mathbf{D}$ taking the form $\delta\mathrm{D} = \sum_i^K \gamma_i k_i$, where k_i is a dummy variable equal to one if the household has $i = 1, ..., K$ children, and zero otherwise. This simplifies the interpretation of results and eliminates the risk of coefficient instability caused by collinearity. The price is the possible introduction of sample selection bias; the modal household with children contains two adults, but only 30% of households fall into this category. As a result "unrestricted" regressions are also run using households with any number of adults, with demographic controls:

$$\delta\mathbf{D} = \delta_1 \ln(n) + \sum_i^K \gamma_i k_i \qquad (6)$$

where n is total household size, and $\sum_i^K \gamma_i k_i$ is defined as above. This specification relates the presence of various numbers of children to total household size in a way that makes extraction of estimated equivalence scales by expressions 4 and 5 straightforward (since we can relate differing child numbers to given reference household sizes). In the event, these unrestricted regressions easily pass the usual multicollinearity tests (Klein's rule of thumb and variance inflation factors [not reported]).

The use of dummy variables for child numbers allows marginal effects to differ by the number of children. Only households with four children or fewer are examined, since sample sizes become too small for reliable inference beyond this number. This excludes 5% of households

[6] For a recent example of Engel curve estimation by Tobit, see Tansel and Bircan (2006). The above latent variable motivation for the Tobit model would be inappropriate if zero values arose for reasons other than optimal non-consumption. A notable possibility is infrequent purchases (Keen 1986). The IE survey approach, and construction of the composite adult good, makes this unlikely to be a problem here (see appendix C.1).

from the analysis.[7]

Demand shifters (**Z**) complete the model. I control for location using province and urban dummies (to capture possible differences in tastes by region which may be correlated with household size, and to capture any relative price variation). Additionally, there are controls for adult age, gender composition, and household education attainment, along which preferences for the composite adult good might vary, along with child numbers. These are the age of the oldest adult, a dummy variable for female-headed households, and the maximum years of formal education attained by any household member. In unrestricted specifications with varying adult numbers, these are supplemented with dummies indicating a majority of adult men or women, against a reference group with equal numbers of men and women (29% of total).

Finally, for equivalence scale derivation by equations 4 and 5, the required parameter values are extracted from Tobit model expected values as the estimated, unconditional marginal effects at relevant household compositions, and the sample means of other variables (excepting other category indicators in a dummy variable set [notably $\sum_i^K k_i$], which are set to zero if applicable). Reported equivalence scales are Tobit regression-based. OLS regressions of restricted and unrestricted specifications with quadratic log expenditure are displayed for comparison with Tobit estimates; these produce very similar scales to those shown.

2.4 Results

Descriptive statistics are presented in table 1. Households with more children naturally contain older children, and are bigger overall. As noted, there is a clear rise in the number of working age women in households with more children. The well-established link between household size and poverty (Lanjouw and Ravallion 1995), driven partly by the growing rural proportion of households with multiple children, is strongly in evidence: total expenditure is higher universally in households with children than households without, but fails to rise over child categories, so that mean per capita spending in four-child households is only a fifth that of zero-child households. Adult goods spending per adult falls consistently across the number of children, most notably between zero- and one-child households (94 to 43 rand), and the proportion of households recording no adult goods spending rises consistently.

Restricted and unrestricted regression results are presented in tables 2 and 3. Quadratic expenditure terms (regressions in all columns except 1.3 and 2.3), are strongly significant. At constant total expenditure, female headship and a majority of women are associated with substantial declines in adult goods spending, while a higher proportion of men (table 3 regressions) is associated with raised adult goods spending. This is consistent with differences in preferences towards adult goods, or in the propensity to spend on children. In restricted specifications, child marginal effects are negative and universally statistically significant. Additional children reduce adult good expenditure progressively less than the previous child category, compared to the zero-child reference group. In fact, 4 children appear to reduce adult goods expenditure slightly *less* than 3, all else equal. F-tests, however, do not reject the hypothesis that 3- and 4-child coefficients are identical. In unrestricted regressions, reported child results are not the full marginal effects of children (since these also work through changes in household size), making them harder to interpret directly. However, costs again appear to plateau quickly after the second child.

[7] Appendix A implements regressions with a continuous child measure for all households.

Table 4 displays resultant equivalence scales. Scales derived from quadratic specifications are expenditure-dependent, with estimated compensating expenditure declining as actual spending rises. Consequently, results at median expenditure per adult for each child category are displayed (deflating expenditure by adult numbers standardises total household resources available to adults, and the median is the best central tendency measure given right-skewed total expenditure). Restricted specifications yield child costs of around half an adult for up to three-child households, with average costs per child declining to a little over a third in four-child households. Unrestricted specifications indicate much higher only-child costs – three-quarters of an adult – and systematic declines in marginal child costs, which are pronounced after the second child (in restricted specifications, this is only in evidence for four children). On average, across households with varying numbers of children, all specifications estimate that children cost in the region of half an adult.

For an indication of the effect of these scales, I simulate paying the compensation for child costs they imply. Unrestricted, quadratic specification estimates (table 3, column 2.2) are used. Figure 3 displays these compensated Engel curves, which indicate appropriate compensation for 1-2 child households (except at very high expenditures where confidence intervals are in any case extremely large). Three- and (especially) four-child households, however, look persistently under-compensated from about halfway through the expenditure distribution, suggesting that the quadratic parameterisation overestimates the expenditure elasticity of adult goods spending for these households, and hence under-compensates at higher expenditure levels. While various ways of addressing this could be considered, the basic message is that compensation appears roughly appropriate by the Rothbarth criterion. These bivariate relationships (figures 2 and 3) are, of course, merely indicative in the sense that they illustrate only a subset of households (those with 2 adults), and neglect systematic differences between households with different child numbers (which motivates multivariate, parametric Engel curve estimation).

3 Children and Adult Time Allocations

3.1 Overview

The above estimates measure child costs as foregone adult consumption at given levels of total spending. This focus on consumption begs the question: what of the time costs of children? Children consume market goods, but they also have care needs (feeding, washing), and add to general household upkeep (cooking, cleaning). Casual empiricism suggests that these costs are substantial, and in fact constitute perhaps the most obvious economic impact of (at least young) children in the household.

The extent to which Rothbarth estimates account for the time costs of children depends on the extent to which adults monetise those costs. This can be explained informally. Figure 4 illustrates the Rothbarth method, plotting adult goods spending against total income (equal to consumption, assuming away any net saving), for otherwise identical households without children (curve K_0) and with children (curve K_1^C). The Rothbarth child cost is the extra consumption needed by the K_1 household to attain the same adult goods spending (A_0) as the K_0 household; this is $C_1 - C_0$.

The value of adult time is implicit in this diagram, since income is a function of market work time. We can thus also think of the illustrated Engel curves as loci of adult spending and work time. If children add to total adult work time (work for commodity consumption plus additional foregone leisure), but not total consumption, this drives a wedge between consumption and total work, and the mappings between adult spending and consumption, and adult spending and work, will no longer correspond. For example, if adults forego leisure to look after children, in addition to working for consumption, adult spending per unit of total work is lower than curve K_1 implies, say K_1^W. In this case, the Rothbarth method underestimates what Apps and Rees (2002) call the "full costs" of children, by $C_2 - C_1$. In contrast, if time costs can be paid for with market work, and adults choose to do so, then the consumption and total work curves coincide, and Rothbarth estimates will capture full costs. For example, parents might forego adult spending, or provide more market labour, in order to pay for a nanny to look after their children. Nanny spending is part of total spending, lowering curve K_1^C, and constituting a captured consumption cost.

If children have time costs, then, the Rothbarth method underestimates the true (full) costs of children, unless time costs happen to be fully monetised. If market and non-market work preferences differ amongst households, this raises the prospect of bias even in estimates intended to capture monetary costs alone. Fully monetising child time costs might, for example, become less appealing as the number of children rises, in which case Rothbarth estimates will overestimate the difference in the costs of children in households with few children relative to those with many. Time costs are also a potential source of the price-like substitution effects of children on adult goods spending which are perhaps the key risk to the consistency of Rothbarth estimates (Deaton 1997). If children do raise the value of adult time (make leisure more precious), they will tend to encourage substitution out of time-intensive consumption goods. If these include adult goods, correctly-compensated adults will still want to substitute away from adult goods consumption, and the Rothbarth method will tend to overestimate welfare-equalising compensation for monetary child costs.

Aside from the issue of potential bias, how serious is the likely exclusion of some (or all) of the time costs of children from the Rothbarth estimates presented thus far? Consumption is certainly the traditional focus of welfare analysis. But reductions in earnings for given foregone leisure, or reductions in leisure for given consumption, while less visible than adult consumption decreases, are real costs. And the less flexible labour and child care markets are, and the more complicated family structures, the less likely it is that a narrow focus on consumption will capture accurately full child costs.

Early studies of the time impact of children examined women's market labour supply and time allocations, applying Becker's extensions of economic theory to within-household production, and emphasis on the importance of the scarce input of time (Gronau 1973, Gronau 1976). Subsequent contributions include Robinson (1987), Gustafsson and Kjulin (1994), Guathier, Smeedeng and Furstenburg (2004) and Burton and Phipps (2007), all of whom find (for nuclear families in rich countries) that children induce large adult time reallocations, primarily for women.

Very few attempts exist to incorporate time into child cost estimates. This is not very surprising, since merging separately-estimated expenditure and time costs into a measure of children's full costs requires a complete understanding of household members' substitutions between market work, non-market work, leisure and consumption. This is easy to see intuitively by figure 4: $C_1 - C_0$ and $C_2 - C_1$ can only be identified if we know the position of both curves K_1^C

and K_1^W. Apps and Rees (2002) provide a detailed description of this problem. Bradbury (2004) attempts to derive equivalence scales from (Australian) time use data, by applying estimated income elasticities of labour to foregone leisure estimates. Johnson and Pencavel (1980), cited in Browning's (1992) survey of the literature on children's economic effects in the household as the only attempt to incorporate time costs in equivalence scales, take a different approach; this informs the regression analysis and time-inclusive equivalence scale calculations to follow.

To examine child time costs for South Africa, I first present evidence from the only time use data for the country - the 2000 TUS – on the associations between children and adult time allocations. This shows that the time costs of children are substantial, tend to reduce total household market work, and are borne almost exclusively by women. Section 4 derives modified scales that, while qualified by data constraints, attempt to account better than traditional Rothbarth scales for the costs implied by adult time substitutions.

Details of the survey, and definitions of the time use measures employed below, are provided in appendix C.2.

3.2 Descriptive Time Use Evidence

The aim is to assess the time impacts of children, under the hypothesis that these entail reallocations of time spent working for commodities consumption (market labour, including subsistence production), production of household services, and leisure. Without imposing any more structure on this question, I begin with the descriptive evidence. Term men and women aged 21 to maximum working age (determined by state pension age eligibility, implying maximum working ages of 59 for women and 64 for men) "prime" adults. Figures 5 and 6 display the proportion of prime adults and children (aged 10-14) engaged in given activities during the 24-hour day, by gender (on days described as typical, for time-keeping "diarists" in households with children). Market work is a significant feature of the day for both men and women, but the proportion of men reporting market work activity is notably higher than women. The reverse is true for non-market work, which looks fairly negligible for men, but very substantial for women. Child care time appears quite low throughout the typical day, but this reflects only direct care (tidying after children, for example, is classified as house work).

For children, market labour appears trivial (except for a small minority of boys in the afternoon), but a material proportion do housework throughout the day, especially girls at breakfast time and in the evening, largely reflecting helping with cooking. Appendix A examines child time allocations in more detail.[8]

Table 5 displays time allocation means, expressed as a proportion of the full (24 hour) day, for working age men and women, by the number of children in the household. For men, there is no indication of a systematic association between time allocations and children. For women, the proportion of time spent on market labour is markedly lower in households with children than childless households (at about 10%, from 16%). We see systematic increases in the proportion of time allocated to household work, rising from 14% in childless households to 19% in four-child households. Similarly, child care time rises systematically, to 5% of total time (72 minutes) in four-child households, while leisure is very slightly lower.

[8] Rama and Richter (2007) and Wittenberg (2005) provide detailed descriptions of children's time use based on the TUS. The latter inspired the use of figures 5 and 6.

Descriptive statistics, then, point to significant differences in time allocation by adult gender, with strong associations between children and the allocations of women (not men).

3.3 Time Allocation Determinants

3.3.1 A Model

A host of intrahousehold labour supply and welfare allocation models could be posited to explain the patterns described above, and guide empirical analysis. However, TUS data limitations are substantial, leading to the likely observational equivalence of most compelling time allocation models. The following simple formalisation therefore suffices for our purposes. The household's problem is:

$$
\begin{aligned}
\max_{x,l_m,l_f} U &= U\left(x,l_m,l_f,n\right) && (7)\\
\text{subject to } px &= y+\sum_{i=m,f} w_i h_i && (8)\\
\text{and } T_i &= l_i+h_i+c_i(n) \text{ for } i=m,f && (9)
\end{aligned}
$$

where x is total commodity consumption at price p, l_m and l_f are the total leisure of men and women, h_m and h_f are the total market labour of men and women at wages w_m and w_f, T_i are total male and female time endowments, and y is non-labour income. There are n children, with time costs given by functions $c_i(n)$, which describe the technology which converts men's and women's time into the household services demanded by children. For simplicity, these time costs are exogenous, and constitute the only form of non-market work. Assuming $c_i(n)>0$, children reduce the time available for market work and leisure. The model is agnostic about the division of total child time requirements between genders (i.e. the determinants of the difference between $C_m(n)$ and $C_f(n)$); allocations may reflect Pareto-efficient labour allocations in the unitary model tradition, or perhaps differences in altruism or bargaining power over the satisfaction of child wants. The consumption and time constraints can be combined through substitution of the h terms into a single budget constraint:

$$
px+\sum_{i=m,f} w_i\left(l_i+c_i(n)\right) = \underbrace{y+\sum_{i=m,f} w_i T_i}_{Z} \qquad (10)
$$

This restricts the total value of commodity consumption, and leisure and child-related time (valued by their market labour opportunity cost) to the family's maximum potential income (given by the market labour value of the total time endowments, plus unearned income). I denote the latter Z and, as is conventional, term this "full income". Consumption and leisure demands are then given by:

$$x^\star = x(p, w_m, w_f, Z, n) \quad (11)$$
$$l_i^\star = l_i(p, w_i, w_j, Z, n) \text{ for } i, j = m, f \text{ and } i \neq j \quad (12)$$

In addition, at the optimum, adults' total work – time devoted to market labour and child wants, the additive inverse of total leisure – is:

$$h_i + c_i(n) = T_i - l_i^\star \text{ for } i = m, f \quad (13)$$
$$\text{or } h_i + c_i(n) = H_i(T_i, p, w_i, w_j, Z, n) \text{ for } i, j = m, f \text{ and } i \neq j \quad (14)$$

Labour and leisure allocations thus respond to children, the price of consumption, and changes in exogenous income, and own or gender counterparts' labour time endowments and earnings.

3.3.2 Empirical Implementation

The above model is brought to the data as faithfully as possible, subject to TUS limitations. Basic household characteristic and resident demographics are available, but more detailed individual data – notably education and employment status – exist only for the one or two time-keeping "diarists" per household. Household and diarist income data are extremely limited, comprising eight- and six-category variables, respectively.

Regressions are run using the sub-sample of prime adults. In lieu of unobserved actual earnings, regressions control for the observable determinants of diarists' market labour productivities (age, age squared, education). Household composition correlates are the number of children (using dummies with zero children as the reference), young adults, other working age men and women, and pension-age residents. Dummies for household proximity to public transport and shops aim to control for variations in fixed work time costs (affecting feasible market labour time).[9] An urban/rural dummy controls for possible consumption cost and work return differences along this divide (including through differential access to on-site water and electrical power). Since the survey was conducted in three tranches over the year 2000, dummies also control for any time fixed effects, as well as for diarists recording their time allocations on weekends, or what they describe as an atypical day (see appendix C.2 for details).

These regressors exclude two important factors. Since the method of their inclusion is debatable, these are added in separate regressions. The first is resident unearned income (y). In 2000, the state pension was the most significant public transfer and, given near-perfect take-up rates and minimal variation in payment amounts, this will be captured by the elderly adult regressors. A remaining, often important, source of non-labour income, however, is private transfers. Its omission is a risk to inference, given the possibility that households with more children attract more remittances (perhaps from absent fathers). TUS respondents are asked whether the household receives such transfers, but the obvious problem is that remittance receipt may be endogenous to adult work allocations. The second is the degree of market labour constraint. For example, holding adult characteristics constant, it might be that larger households with more

[9]Dummy variables take on a value of one if public transport (train, bus or taxi) or shops are within a thirty minute (2 km) walk.

children tend to be located in areas with lower employment opportunities, attenuating child impact estimates if children raise the need, but not the capacity, for earnings. In the absence of valid instruments for private transfers and unemployment status, I resort to adding the former as a dummy variable, and the latter using the district-level unemployment rate (as a "less endogenous" proxy for individual involuntary unemployment).

Given the descriptive evidence, reflected in model choice, that time allocations are very different for men and women, separate regressions are run by gender. Note that the model above is agnostic on the apportionment of work and leisure time amongst adults of the same gender, and (as discussed) apportioning of total child time costs amongst men and women. The limitations of the TUS mean that little can be done to improve on this (or, indeed, examine the broader question of whether explicitly collective models of allocation between genders would better describe household decision-making processes). In consequence, observed associations between work and factors like education and age may reflect not only labour productivity, but bargaining power over welfare allocation.

An appealing starting point for regression analysis – a partial correlation counterpart to the descriptive statistics of section 3.2 – is seemingly unrelated regression ("SUR", Zellner (1962). See Wooldridge (2002), ch. 7). I regress market work, non-market work and leisure time on the above regressor set, allowing for error correlation arising from the use of related dependent variables and a single observation set. Given identical regressors, this is equivalent to estimating separate OLS equations, but makes residual correlation, and the joint significance of variables of interest in time allocations, straightforward to examine. Leisure must either be defined as all non-work time in the 24-hour day, or those activities likely to yield utility directly, with total time endowment T net of all other, non-work activities. I opt for the latter, since the former is simply the additive inverse of the total work measure described and implemented below.

Examining market work, non-market work and leisure time yields insights into the influence of children, but not a unified view of their net impact. The model suggests that an appropriate measure of this net effect is total work, defined as the sum of market and non-market work. Further, a weakness of the SUR estimates is the large number of zero values. The proportion of prime age men and women respectively reporting no market work on a typical week day is 29% and 52%, and 24% and 3% report zero non-market work. Zero values are much less common when total work is considered: 5% of male observations, and just 0.3% of female (5 cases). For these reasons, regression analysis is also conducted with total work as the dependent variable.

Section 3.3.3 presents regression estimates of market, non-market work and leisure. Section 3.3.4 outlines the empirical modeling approach for total work, and presents results.

3.3.3 Market Work, Non-Market Work and Leisure: SUR Results

SUR child coefficients and their joint significance across time allocations are reported in table 6, and complete results and residual correlations in tables 7 and 8. The pattern suggested by table 5 is broadly upheld. Children are jointly insignificant in male time allocations using these categories, with the exception of four children (significant at the 10% level), who are associated with just over an hour more market work, and 42 minutes less leisure, than is the case in otherwise identical zero-child households. In contrast, female time allocations look very sensitive to children, with lower market labour time of between about half an hour and an hour, consistently increasing non-market work time (75 minutes more than with zero children for one child, rising to 111 minutes for four children), and reduced leisure.

Correlation matrices (table 8) indicate strong correlations in equation residuals. While this is expected since these categories together account for the lion's share of total non-sleep time, an interesting pattern emerges. Unobserved factors driving up the market work of men tend to drive down non-market work and (especially) leisure (-0.68 correlation). The pattern for women is similar, but the correlation between market and non-market work residuals is significantly stronger for women than men (-0.52 versus -0.35). This suggests a tighter relationship between market and non-market work for women, and between market work and leisure for men.

3.3.4 Total Work: Tobit and OLS Results

Figure 7 displays histograms of prime adult work time densities. For graphical clarity, these are conditioned on positive work time in the relevant category (so the fact that there are sometimes large density masses at zero should not be forgotten). For market work, conditional work time distributions are reasonably smooth, peaking at around 8-10 hours (considerably more pronounced for men). This reflects standard working days for those in full-time employment. The density of non-market work time tapers off very quickly for men, but there is much more variation for women, with the density declining only slowly until around the six hour mark. Total work time is reasonably close to normally distributed for women, but rather bimodal for men – men are considerably more likely to provide very little total work, or work around a full, standard working day, than anything in between.

The reason is illustrated by figures 8 (joint density estimates of market and non-market work, by gender) and 9 (a scatter plot by gender). The former is more informative but entails smoothing the data, so the latter is included to display the data in raw form. Men tend to do much more market work than women, while women do much more non-market work. Market work accounts for 67% of total male work on typical weekdays, against 33% for female. The more of one kind of work someone does, the less they tend to do of the other, but the relationship is much stronger for women (market/non-market work correlation of -0.55) than for men (-0.35). The figures suggest that much of this is due to the fact that most women who do little or no market work do a lot of non-market work, but the same is not true of men. One consequence is that women work more on average (by a statistically significant 30 minutes on a typical day).

The implication is that the notion of market/non-market work substitutability on which the total work measure is premised appears much more plausible for women than it does for men. The 131 minutes of non-market work performed on average by men doing no market work (compared to 323 minutes for women), in other words, is unlikely to be comparable to roughly two hours of market labour. It might be that men's non-market labour productivity is very low, or that social norms prevent men from providing much non-market work.

Led by the data, I thus assume that female work is well described by the unadjusted total work measure, which is close enough to normally-distributed to be amenable to analysis by straightforward OLS or GLM.[10] For men, however, there is an important distinction between

[10]Inadequate kurtosis results in the rejection of female total work normality by formal tests; but it appears close enough for comfort. OLS results are reported. One weakness of these is that some predicted total work values are negative. An alternative, which avoids this problem, is a fractional logit approach. This expresses time as a proportion (as in table 5), with estimation by generalised least squares using a logit link function, following Papke

the (typically limited) work of men who provide no market work, and those providing it. This is addressed by applying a generalised Tobit model to a modified work variable (W) where:

$$W = \begin{cases} W_T & \text{if } W_m > 0 \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

where W_T is total work and W_m is market work. That is, we assume substitutability of market and non-market work for employed men only, and treat the outcomes of the unemployed separately. In practise, this is almost the same as considering male market labour only (the total work/market work correlation for men is 0.92), and $W|W_m > 0$ is very close to normally distributed. Dividing the density into two parts and applying a Tobit model is justified by the uncontroversial assumption that the disproportional density mass at zero market work arises primarily from involuntary unemployment. In the absence of compelling exclusion restrictions (observed factors influencing employment probability but not labour supply conditional on employment) which would allow for employment probability and total work to be modeled flexibly as jointly determined (in the manner of Heckman's selection model), we have little choice but to require observables to have the same impact on employment probability and conditional labour supply.[11]

Table 9 displays results for men and women, without (columns 1.1 and 2.1) and with (1.2 and 2.2) remittance and unemployment controls. Coefficient signs generally conform to priors, and discussion focuses on results for the child dummies. These are statistically insignificant for men, suggesting – much like the descriptive statistics and SUR estimates above – that male work tends to be insensitive to the presence of children. For women, on the other hand, more children are associated systematically with more total work than the no-child case, all else equal. Coefficients are higher (especially for the fourth child) when remittances and involuntary unemployment are present as controls (column 2.2). In fact, unemployment is not statistically significant for women, while the remittance dummy coefficient is large, negative and strongly significant. Given this negative sign, the pattern of larger child coefficients is consistent with omitted variable bias when remittances are excluded, if (as seems likely and is the case under bivariate comparison) children and remittances are positively associated.

3.3.5 Results Summary

The preponderance of dummy variables in these regressions places rather heavy demands on the data. However, these regressions provide evidence that children reduce the market labour supply, and increase the non-market labour supply, of women. The latter dominates, so that women's total work time (the additive inverse of leisure) rises with children, on average. This effect is material: by regression 2.2, women's total work is half an hour higher in one child households than in zero child households, and over an hour and twenty minutes higher when there are four children, all else equal. There is no directionally robust variation in men's time

and Wooldridge (1996). Results are nearly identical.

[11] Obvious alternatives would be to (1) run OLS for observed male work, knowing that this will be biased by a substantial failure of the normality assumption, or (2) assume a two-part model (e.g. a probit on employment probability and OLS on positive work time), ignoring the selection bias in the latter's coefficients that would likely arise as a result.

allocations with children, but a caveat is that men's work time allocations are considerably more difficult to model than women's. The likely explanation is that men's work experiences are dominated by whether or not they have full-time jobs, rather than substitutions between market and non-market labour. Nevertheless, the lack of any robust correlations between male work and children certainly suggests that child time burdens fall squarely on women.

4 Full Income-Based Equivalence Scales

Equivalence scales that incorporate child time costs are not standard, but the evidence suggests that they should be. One way of achieving this is suggested by the model of section 3.3.1. Considering the optimal consumption and leisure expressions, we see that the expenditure function can be written as:

$$Z = e(w_m, w_f, p, n; U^\star) \tag{16}$$

This expresses the full income (Z) needed to obtain some utility $U^\star$, at given wages, prices, and child numbers. Just as the conventional Rothbarth method uncovers the ratio in total expenditure between a childless reference household and household with children needed to equalise adult goods spending, we can ask: what ratio in full incomes is needed for a household with children to attain the reference household's utility? It remains to define reference utility. A straightforward option – in the tradition of the Rothbarth method – is to assume that households with equal adult goods spending are equally well-off.

We can thus duplicate the Rothbarth method of section 2, using full income as the household resource constraint instead of total expenditure.[12] Estimated child costs, in this case, reflect the additional full income adults with children would need to consume the same value of adult goods as adults without children, all else equal. If children eat into adult leisure and market work in the manner indicated by the time use data, raising leisure value, accounting for this should boost the estimated compensation required to equalise adult goods spending. Full income based scales, then, should be higher than Rothbarth estimates.

4.1 Implementation

The above method presupposes reliable estimation of full income. In practise, it is difficult to infer maximum potential labour earnings. This is true both of earners (whose choices may be constrained by labour market rigidities that call into question the extent to which observed hourly earnings are the opportunity cost of leisure), and non-earners, for whom potential earnings must be inferred. This unavoidable limitation qualifies this section's results.

To obtain full income, the IES and LFS are merged, after which we observe both individual earnings, and total income and expenditure.[13]

[12] The same idea is the subject of Johnson and Pencavel (1980) (see especially appendix for an analogous, structural alternative – enabled by rich data from the US basic income experiments – to the simpler reduced-form approach adopted here) and Van Hoa and Ironmonger (1989).

[13] Household-level earnings are available in the IES. But the LFS, since it is dedicated to labour data, provides earnings data which are likely to be of higher quality (Punt 2005), and detail on hours worked, which allows for more accurate estimation of individuals' full incomes.

Earnings prediction is complicated by high involuntary unemployment. For our purposes, this means that a non-earner's expected labour income is not the mean earnings of those with identical characteristics who are earning, but that value adjusted for the probability that, conditional on wanting to sell labour, the individual is able to do so. Ideally, we would want to predict earnings by modeling the determinants of employment and earnings conditional on employment, recognising the likely correlations between unobserved factors contributing to these outcomes. However, we are interested only in the average opportunity cost of time for given observable characteristics, rather than the marginal effects of particular outcome determinants. Attempting to estimate a sophisticated selection model is both unlikely to be successful and, even if successful, unlikely to add very much more value than a simpler approach for the task at hand. Consequently, predicted earnings are obtained from simple OLS regressions of unconditional earnings (zero if unemployed) on age and age squared (to capture possibly non-linear experience effects), education (including a quadratic term [see footnote]), and location (provincial, and urban/rural). Weighted samples of employed and involuntarily unemployed prime adults are used, and regressions estimated separately for men and women.[14] Table 10 reports results, which appear similar to those obtained by Brathaug and Budlender (2005), who use the TUS and LFS to provide macro estimates of the value of unpaid work. The mean predicted earnings of prime men and women are 6.56 and 4.28 rand an hour.

Full income is assigned using observed hourly earnings for earners, and predicted hourly earnings from these regressions for non-earning, working age residents. Productive monthly time endowments of 308 hours are assumed for all working age adults:
14 hours/day $\times$ 22 working days/month. State pension income is included as unearned income, where observed.

4.2 Results

Results are reported in tables 11 and 12 (restricted and unrestricted specification regressions), and table 13 (equivalence scales). Regressions perform well, with adult goods spending displaying the same non-linear relationship with full income constraints as for expenditure, and other regressors largely robust to the substitution of full income for expenditure. Equivalence scales display the same patterns, but are about twice as large, as those obtained using the conventional Rothbarth method (table 4), with mean adult equivalence around one. An estimate suggesting that a child's economic impact in a household is similar to that of an additional, economically-unproductive adult may seem implausibly high at first glance. But, as noted by Bradbury (2004), this figure is unsurprising once the unconventional inclusion of time costs is digested; adult consumption may be considerably more expensive than children's, but adult time costs are minimal in comparison.

The use of full income as the measure of household resources against which to assess child costs as the drop in adult goods spending is clearly not without difficulties. Unlike expenditure

[14] A common approach to earnings function estimation for South Africa, given high unemployment, is to impose a Tobit model. See Keswell and Poswell (2004) for a survey (from a returns to education perspective). However, given severely right-skewed earnings, error terms are not likely to be normal, with potentially severe consequences for estimator consistency, that could easily be worse than OLS bias. Dependent variable transformations such as ln(1 + earnings) may alleviate this, but this is somewhat arbitrary, and makes recovering predicted earnings difficult. Separately, note too that the apparent strong convexity in the returns to education obtained here is in line with the evidence surveyed by Keswell and Poswell (2004).

(which is observed), it has to be estimated. This involves combining observed and predicted earnings, and using these to infer the value of time, which requires assumptions about total time endowments, and the extent to which hourly earnings could hypothetically be obtained for more time than is actually the case. Measurement error, then, is likely to be very substantial. In addition, regressions ignore residents' unearned income which risks being endogenous, notably private transfers.[15] Nevertheless, the fact that full income-based estimates are about twice expenditure-only figures indicates that time costs are likely close to monetary costs alone.

5 Conclusion

5.1 Discussion of Results

This paper has evaluated child costs using expenditure, time use and labour force data. Child consumption is estimated to cost about half of an adult's on average, based on children's impact on adult goods spending. The time cost of children appears to fall squarely on women, with no discernable effect on men's time allocations at the aggregation levels considered. The adult equivalence of children rises to about one on average, when time costs are taken into account.

There is some evidence of decreasing marginal child costs, primarily in unrestricted specifications. There are a number of possible explanations. First, there may be economies of scale in child consumption. These may be static (younger children inherit older siblings' clothes), or dynamic (child costs decline on the margin as parents learn by doing). In this respect, note that estimated scales differ in their treatment of general household scale economies. In restricted specifications, child costs are measured against the hypothetical addition of an adult costing the same as adults in the reference (2-adult) household. These scales thus embed any general consumption scale economies that accrue to households which add members. In unrestricted specifications, on the other hand, predicted adult good expenditure incorporates general household size effects – including for the 2-adult reference household – so child cost estimates are net of some potential scale economies. This is a likely explanation for the higher average estimates produced by unrestricted specifications (on the order of 10%). If the aim is to understand the resource burden placed on adults by additional children (as opposed to the notion of an intrinsic child cost), it is appropriate to embed economies of scale in the estimated impact of the marginal child; in this case, restricted specification estimates may be most accurate.

Second, households with more children generally contain older children. Older children's commodity consumption wants are surely greater than smaller children's. But they may also have lower time costs, and earn income or assist with house work and care of younger siblings. Appendix A provides some evidence. This issue again makes it important to distinguish between different uses of child cost estimates. If the aim is to compensate parents for expenditure and time losses, embedding children's resource contributions in cost estimates is appropriate. If the aim is to use estimates to standardise welfare comparisons between (all) individuals living in different kinds of households, such estimates will overstate welfare in many-child households.

Third, adults in households with different numbers of children might have different, unobserved preferences over children. In particular, parents may have different attitudes to child "quality" and quantity, trading off a relatively invariant total allocation of resources for children

[15]In practise, the inclusion of private transfer income (obtainable from the IES) has little impact.

amongst different numbers of children, according to preference (Becker 1960). If this is the case, estimated costs for the first child will be the most accurate indicator of the marginal impact of a child. Again, the intended use of child cost estimates is crucial.

Unobserved heterogeneity is, of course, a more general issue when trying to reach causal conclusions using cross-sectional data such as these. Households with different numbers of children may simply be systematically different in unobserved ways. To take one (not especially compelling) example: the low marginal cost of the fourth child could reflect systematically stronger preferences for adult goods amongst adults in households with four children. Another, in time use regressions, is the possibility that fertility is endogenous to income and, hence, work time (though if this is the case, child coefficients remain useful child cost indicators). A more serious limitation of time use estimates is unobserved migrant labour supply; the TUS gathers no information on non-resident workers, who are likely to be men. If children raise migration probability for men, observed resident male work associations may be misleading. The large, negative coefficient on the remittance dummy in male work regressions (table 9), for example, may be partly due to a resident male selection effect.

5.2 Why the Choice Matters, and a Recommendation[16]

Child cost measurement choice matters for distribution estimates whenever child numbers differ systematically along the dimension of interest. Table 5 is evidence that this is very likely to be the case: households with more children are much more likely to be rural, and total expenditure fails to rise with children, indicating that their members are almost certainly worse off on average. If poorer households contain more children, household composition standardisations that underestimate child costs understate poverty, and *vice versa*.

For an indication of the quantitative importance of cost measures for static inequality estimates, figure 10 displays generalised Lorenz curves, based on assigning equivalence scales of the form (1) that given by equation 1 (children equivalent to half an adult, with weak scale economies), (2) $\frac{x}{n^{0.9}}$ (where n is household size, i.e. adult-equivalent children, with weak scale economies), and (3) $\frac{x}{n}$ (per capita expenditure). Estimated inequality is higher for each measure in succession; Gini coefficients are 0.52, 0.54 and 0.56.

Simple poverty measures display a similar pattern. Using the international one (extreme poverty) and two dollars per person (or adult equivalent, for (1) and (2) per day poverty lines), the (extreme) poverty headcount ratios under the three scales above are 46% (18%), 52% (24%), and 56% (30%). Per capita expenditure produces estimates well above those embodying household scale economies, and estimated poverty levels increase tangibly with increases in assumed child costs.

On balance, the child cost estimates produced here are likely to be conservative. Rothbarth estimates are usually suspected of underestimating costs, because of the possibility that children have substitution effects which favour the adult goods basket (Barten 1964). Work time estimates are based on demanding assumptions, the most extreme of which is unconstrained market labour supply choice; if the proxy unemployment variable does not partial this out completely, the estimates presented are attenuated. Considering this paper's results in this light suggests that the commonly-used half an adult rule of thumb for average child costs, in conjunction with modest

[16] All calculations based on the black, probability-weighted sub-sample of the 2000 IES.

general household scale economies, is meager. Something like three-quarters – or perhaps even unity, with small, general scale economies – would be an improvement.

TABLE 1: DESCRIPTIVE STATISTICS BY NO. OF CHILDREN (MEANS, STD. DEVIATIONS IN BRACKETS)

Children	None	One	Two	Three	Four
Child demographics					
Age of oldest child	.	7.22	9.84	11.27	11.91
	(.)	(4.52)	(3.30)	(2.52)	(2.05)
Child gender mix (girls/kids)	.	0.48	0.50	0.49	0.52
	(.)	(0.50)	(0.36)	(0.29)	(0.25)
Adult demographics					
Total HH size	1.85	3.88	5.06	6.38	7.66
	(1.23)	(1.50)	(1.64)	(1.75)	(1.89)
Young adults (15-20)	0.24	0.64	0.74	0.83	0.98
	(0.57)	(0.83)	(0.88)	(0.93)	(0.97)
Men (21-64)	0.87	0.88	0.87	0.88	0.88
	(0.73)	(0.85)	(0.88)	(0.88)	(0.95)
Women (21-59)	0.57	1.09	1.17	1.33	1.43
	(0.71)	(0.68)	(0.75)	(0.87)	(0.88)
Elderly men (65+)	0.05	0.07	0.08	0.07	0.10
	(0.23)	(0.26)	(0.27)	(0.27)	(0.30)
Elderly women (60+)	0.12	0.20	0.21	0.26	0.28
	(0.33)	(0.41)	(0.43)	(0.46)	(0.47)
Age of oldest prime adult	38.78	41.57	41.63	42.26	42.23
	(10.80)	(10.68)	(10.16)	(9.84)	(9.65)
HH Location and Expenditure					
Urban	0.70	0.60	0.53	0.44	0.34
	(0.46)	(0.49)	(0.50)	(0.50)	(0.47)
Total expenditure	1569.17	1803.78	1775.62	1772.94	1651.93
	(1491.10)	(1782.67)	(1721.82)	(1718.68)	(1525.38)
Expenditure per capita	1061.16	496.72	369.45	287.80	218.80
	(1128.91)	(524.67)	(382.47)	(294.29)	(202.08)
Total adult goods	136.38	112.34	93.73	84.99	79.39
	(202.76)	(191.46)	(158.15)	(137.68)	(132.88)
Adult goods per adult	93.60	42.80	35.02	27.48	23.21
	(145.95)	(72.99)	(61.20)	(46.13)	(40.01)
Zero adult goods spending (prop.)	0.15	0.22	0.26	0.28	0.28
	(0.36)	(0.41)	(0.44)	(0.45)	(0.45)
Observations	8349	3830	3474	2253	1184

Notes: Weighted sample means. All expenditure variables in rand per month.

TABLE 2: ROTHBARTH REGRESSIONS OF COMPOSITE ADULT GOOD EXPENDITURE IN 2-ADULT HOUSEHOLDS: OLS AND TOBIT, ON QUADRATIC AND LINEAR (1.3) LOG EXPENDITURE

	1.1 OLS	1.2 Tobit	1.3 Tobit
Urban (d)	-9.835^{*}	-9.778^{*}	-8.542^{*}
	(4.450)	(3.940)	(3.901)
Education (max. yrs.)	0.891	0.261	0.100
	(1.066)	(0.862)	(0.892)
Female HH head (d)	-43.482^{**}	-40.341^{**}	-40.837^{**}
	(4.522)	(3.740)	(3.724)
Oldest adult age	-0.524^{**}	-0.418^{**}	-0.459^{**}
	(0.140)	(0.128)	(0.131)
1 child (d)	-19.556^{**}	-19.584^{**}	-19.392^{**}
	(6.087)	(5.198)	(5.258)
2 children (d)	-37.246^{**}	-38.199^{**}	-38.126^{**}
	(6.697)	(5.484)	(5.433)
3 children (d)	-55.907^{**}	-53.403^{**}	-52.822^{**}
	(6.254)	(5.227)	(5.182)
4 children (d)	-42.365^{**}	-47.347^{**}	-47.993^{**}
	(8.327)	(7.369)	(7.337)
Ln(expenditure)	-229.489^{**}	-72.875^{*}	86.331^{**}
	(43.605)	(35.625)	(3.694)
$(\text{Ln(expenditure)})^2)$	22.842^{**}	11.073^{**}	
	(3.314)	(2.651)	
Province controls	Yes	Yes	Yes
N, 0-censored		1153	1153
Total N	5681	5681	5681
F	91.6^{**}	66.2^{**}	55.0^{**}
Pseudo-R^2 ($\hat{A}$ vs. A)	0.337	0.350	0.351

2-adult HHs with ≤ 4 children. Child dummy reference category is zero children. Sample weights used. Tobits display unconditional marginal effects at the mean (or 0 to 1 change for discrete variables, with all other [non-category] variables at the mean). Std. errors are heteroskedasticity-robust. $^{+}$, *, ** denote significance at 0.10, 0.05 and 0.01 levels. d indicates dummy variable.

TABLE 3: ROTHBARTH REGRESSIONS OF COMPOSITE ADULT GOOD EXPENDITURE IN ALL HOUSEHOLDS: OLS AND TOBIT, ON QUADRATIC AND LINEAR (2.3) LOG EXPENDITURE

	2.1 OLS	2.2 Tobit	2.3 Tobit
Urban (d)	2.370	0.076	1.653
	(3.042)	(2.521)	(2.525)
Ln(HH size)	17.476**	10.523**	10.595**
	(4.609)	(3.529)	(3.547)
Education (max. yrs.)	−1.013+	−0.840*	−0.990*
	(0.521)	(0.412)	(0.416)
Female HH head (d)	−17.021**	−19.486**	−20.930**
	(3.541)	(2.831)	(2.818)
Oldest adult age	−0.551**	−0.357**	−0.415**
	(0.093)	(0.076)	(0.078)
Majority men (d)	17.682**	11.454**	11.525**
	(4.240)	(3.291)	(3.307)
Majority women (d)	−16.121**	−14.669**	−14.032**
	(3.410)	(2.825)	(2.830)
1 child (d)	−35.195**	−33.254**	−32.838**
	(5.279)	(4.359)	(4.397)
2 children (d)	−55.831**	−52.086**	−52.346**
	(6.386)	(5.184)	(5.205)
3 children (d)	−64.543**	−58.997**	−59.478**
	(7.192)	(5.936)	(5.964)
4 children (d)	−65.486**	−59.617**	−60.749**
	(8.182)	(6.892)	(6.935)
Ln(expenditure)	−233.004**	−101.940**	88.291**
	(37.310)	(19.495)	(2.054)
$(\text{Ln(expenditure)})^2$)	23.737**	13.403**	
	(2.710)	(1.439)	
Province controls	Yes	Yes	Yes
N, 0-censored		3949	3949
Total N	18829	18829	18829
F	120.2**	98.2**	90.8**
Pseudo-R^2 ($\hat{A}$ vs. A)	0.298	0.308	0.305

All HHs with ≤ 4 children. Child dummy reference category is zero children. Sample weights used. Tobits display unconditional marginal effects at the mean (or 0 to 1 change for discrete variables, with all other [non-category] variables at the mean). Std. errors are heteroskedasticity-robust. $^{+}$, *, ** denote significance at 0.10, 0.05 and 0.01 levels. d indicates dummy variable.

TABLE 4: EXPENDITURE-BASED ROTHBARTH METHOD EQUIVALENCE SCALES

Children	One	Two	Three	Four	Mean
Total adult equivalence					
Restricted, linear	1.252	1.555	1.844	1.744	.
Restricted, quadratic	1.264	1.557	1.836	1.742	.
Unrestricted, linear	1.377	1.654	1.736	1.712	.
Unrestricted, quadratic	1.379	1.623	1.689	1.658	.
Average adult equivalence per child					
Restricted, linear	0.504	0.555	0.563	0.372	0.498
Restricted, quadratic	0.528	0.557	0.557	0.371	0.503
Unrestricted, linear	0.754	0.654	0.490	0.356	0.564
Unrestricted, quadratic	0.759	0.623	0.459	0.329	0.542

Scales are $\frac{x_i}{x_0}$, where x_0 is expenditure in a 2-adult, 0-child reference household and x_i is expenditure in a 2-adult, i-child household. Scales are expenditure-dependent in quadratic specifications; estimates at median total expenditure per adult in HHs with given numbers of children reported.

TABLE 5: PROPORTION OF TOTAL TIME SPENT ON ACTIVITIES: MEANS (STD. DEVIATIONS IN PARENTHESES)

	Pooled					**Men (21-64)**					**Women (21-59)**				
Children	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Market work	0.20	0.13	0.14	0.13	0.14	0.23	0.17	0.20	0.20	0.22	0.16	0.10	0.11	0.09	0.09
	(0.20)	(0.17)	(0.19)	(0.18)	(0.18	(0.20)	(0.19)	(0.20)	(0.19)	(0.21	(0.19)	(0.16)	(0.17)	(0.15)	(0.15)
HH work	0.10	0.13	0.13	0.13	0.15	0.07	0.07	0.05	0.04	0.07	0.14	0.17	0.17	0.19	0.19
	(0.09)	(0.11)	(0.12)	(0.12)	(0.12	(0.08)	(0.09)	(0.08)	(0.06)	(0.11	(0.10)	(0.11)	(0.12)	(0.11)	(0.11)
Child care	0.00	0.02	0.03	0.03	0.03	0.00	0.00	0.00	0.01	0.00	0.00	0.04	0.04	0.05	0.05
	(0.01)	(0.05)	(0.05)	(0.06)	(0.06	(0.01)	(0.02)	(0.01)	(0.03)	(0.01	(0.02)	(0.06)	(0.05)	(0.07)	(0.07)
Sleep	0.39	0.39	0.39	0.39	0.40	0.38	0.39	0.39	0.38	0.38	0.40	0.40	0.40	0.40	0.41
	(0.09)	(0.08)	(0.08)	(0.08)	(0.07	(0.09)	(0.09)	(0.09)	(0.09)	(0.08	(0.10)	(0.07)	(0.08)	(0.08)	(0.06)
Leisure	0.26	0.27	0.25	0.25	0.25	0.27	0.32	0.30	0.30	0.29	0.25	0.25	0.23	0.22	0.23
	(0.14)	(0.14)	(0.14)	(0.13)	(0.14	(0.14)	(0.15)	(0.16)	(0.14)	(0.16	(0.13)	(0.12)	(0.12)	(0.11)	(0.11)
Other	0.05	0.05	0.05	0.06	0.04	0.05	0.05	0.06	0.08	0.04	0.05	0.05	0.05	0.05	0.04
	(0.07)	(0.07)	(0.08)	(0.09)	(0.04	(0.07)	(0.07)	(0.09)	(0.11)	(0.04	(0.07)	(0.07)	(0.07)	(0.07)	(0.04)
Observations	3440	2119	1825	1148	541	1994	869	716	469	226	1446	1250	1109	679	315

Notes: Weighted means for days described as typical. Categories are mutually exclusive and exhaustive.

TABLE 6: SU REGRESSION ESTIMATES: TIME ALLOCATION (MINUTES) - CHILD DUMMY ASSOCIATIONS

	Mkt. work	Non-mkt. work	Leisure	Joint sig.
Men (21-64)				
1 child	−9.476	4.468	13.553	2.88
	(13.800)	(6.070)	(10.796)	
2 children	6.326	−9.801	−2.009	2.29
	(15.674)	(6.895)	(12.262)	
3 children	32.977^{+}	−12.406	−3.516	4.61
	(19.395)	(8.531)	(15.173)	
4 children	67.985*	6.082	−42.317^{+}	7.39^{+}
	(29.168)	(12.830)	(22.818)	
Women (21-59)				
1 child	−36.797**	75.600**	−13.863^{+}	96.85**
	(10.461)	(7.906)	(8.040)	
2 children	−47.338**	87.854**	−7.564	117.02**
	(11.190)	(8.456)	(8.599)	
3 children	−54.774**	122.142**	−38.342**	137.11**
	(14.103)	(10.658)	(10.838)	
4 children	−32.830^{+}	111.353**	−39.318**	66.70**
	(19.159)	(14.480)	(14.725)	

HHs with ≤ 4 children. Child reference category is 0 children. Joint significance figures are Chi-squared test statistics. $^{+}$, *, ** denote significance at 0.10, 0.05 and 0.01 levels.

TABLE 7: SEEMINGLY UNRELATED REGRESSIONS: TIME ALLOCATION (MINUTES)

	Men (21-64)			**Women (21-59)**		
	Mkt. work	Non-mkt. work	Leisure	Mkt. work	Non-mkt. work	Leisure
Saturday	−150.747**	7.264	122.067**	−86.953**	13.229	75.541**
Sunday	−226.908**	−0.091	171.452**	−137.323**	−20.236*	115.606**
Atypical day	−101.356**	2.091	41.584**	−55.767**	−6.929	19.433*
Unemployment	−273.159**	87.808**	146.903**	−166.661**	121.191**	14.153
Rcv. remittances	−183.230**	36.097**	81.984**	−125.891**	31.438**	45.837**
Age	18.512**	−1.987	−3.267	20.324**	−5.221*	−4.230^{+}
Age squared	−0.237**	0.026	0.047	−0.214**	0.040	0.056^{+}
Education (yrs.)	−1.086	0.057	4.412**	6.767**	−3.032**	0.510
Urban	19.752	−14.762**	0.344	−8.636	−34.863**	30.240**
Transport nearby	−57.926**	16.741*	22.999^{+}	−2.586	−15.090	16.582
Shops nearby	−18.453	1.252	19.925^{+}	−2.456	2.920	1.170
Young adults	2.515	0.078	−2.217	−2.908	−16.018**	11.837*
Men 21-64	−29.222**	7.623*	21.407**	−33.177**	19.897**	15.602**
Women 21-59	−34.004**	−26.857**	38.454**	6.788	−40.662**	17.740**
Men 65+	−22.162	12.969	21.331	−66.265**	68.807**	−38.185*
Women 60+	−86.389**	−19.552*	67.914**	−37.090*	−0.710	37.193**
1 child	−9.476	4.468	13.553	−36.797**	75.600**	−13.863^{+}
2 children	6.326	−9.801	−2.009	−47.338**	87.854**	−7.564
3 children	32.977^{+}	−12.406	−3.516	−54.774**	122.142**	−38.342**
4 children	67.985*	6.082	−42.317^{+}	−32.830^{+}	111.353**	−39.318**
Tranche controls	Yes	Yes	Yes	Yes	Yes	Yes
N	2868			3021		
Chi-squared	839.9	184.0	634.7	613.4	460.1	402.4
Adj. R^2	0.23	0.06	0.18	0.17	0.13	0.12

HHs with ≤ 4 children. Child reference category is 0 children. $^{+}$, *, ** denote significance at 0.10, 0.05 and 0.01 levels.

TABLE 8: SU REGRESSIONS: RESIDUAL CORRELATION MATRICES

	Mkt. work	Non-mkt. work	Leisure
Men (21-64)			
Market work	1.0000		
Non-market work	−0.3497	1.0000	
Leisure	−0.6758	−0.0699	1.0000
Breusch-Pagan test of independence (χ^2-statistic)		1674.406**	
Women (21-59)			
Market work	1.0000		
Non-market work	−0.5174	1.0000	
Leisure	−0.4882	−0.1817	1.0000
Breusch-Pagan test of independence (χ^2-statistic)		1628.510**	

TABLE 9: TOBIT AND OLS REGRESSIONS: TOTAL WORK (MINUTES), PRIME AGE MEN AND WOMEN

	1.1 Tobit Men	1.2 Tobit Men	2.1 OLS Women	2.2 OLS Women
Atypical day (d)	-125.678^{**}	-123.063^{**}	-59.454^{**}	-62.777^{**}
	(19.823)	(19.664)	(13.267)	(13.181)
Saturday (d)	-153.160^{**}	-155.121^{**}	-95.340^{**}	-96.570^{**}
	(19.822)	(18.672)	(16.623)	(16.618)
Sunday (d)	-218.112^{**}	-219.523^{**}	-144.728^{**}	-146.720^{**}
	(17.197)	(16.039)	(12.272)	(12.157)
Age	29.002^{**}	21.660^{**}	17.790^{**}	15.768^{**}
	(5.265)	(5.120)	(3.477)	(3.497)
Age squared	-0.362^{**}	-0.280^{**}	-0.206^{**}	-0.185^{**}
	(0.065)	(0.063)	(0.046)	(0.046)
Education (yrs.)	-1.867	-2.067	4.294^{**}	3.563^{*}
	(2.406)	(2.297)	(1.444)	(1.427)
Urban (d)	32.144^{+}	27.541	-39.751^{**}	-46.753^{**}
	(18.163)	(18.143)	(10.604)	(10.878)
Transport nearby (d)	-90.272^{**}	-83.562^{**}	-6.493	-4.662
	(26.934)	(27.065)	(16.643)	(17.213)
Shops nearby (d)	-26.714	-6.719	-8.596	-2.873
	(23.828)	(22.792)	(14.933)	(15.147)
Young adults	2.623	4.832	-12.694^{+}	-9.287
	(13.086)	(12.575)	(6.907)	(7.102)
Men 21-64	-24.442^{+}	-30.333^{*}	-13.467^{*}	-21.939^{**}
	(12.787)	(12.419)	(6.495)	(6.808)
Women 21-59	-51.027^{**}	-56.903^{**}	-26.858^{**}	-27.841^{**}
	(14.194)	(13.974)	(7.167)	(7.055)
Men 65+ (d)	68.158	59.104	-30.387	-39.022
	(62.731)	(57.330)	(28.262)	(28.450)
Women 60+ (d)	-72.296^{*}	-70.002^{*}	-32.067^{+}	-41.956^{*}
	(30.712)	(31.026)	(18.679)	(18.633)
1 child (d)	-30.524	-34.816	26.778^{*}	30.907^{*}
	(23.683)	(22.597)	(12.801)	(12.604)
2 children (d)	-14.749	-15.504	45.735^{**}	52.720^{**}
	(24.211)	(24.047)	(13.944)	(13.645)
3 children (d)	23.043	31.767	56.157^{**}	61.727^{**}
	(29.578)	(30.153)	(16.357)	(16.149)
4 children (d)	55.723	48.901	68.969^{**}	82.519^{**}
	(57.984)	(53.622)	(21.040)	(21.567)
Unemployment		-254.800^{**}		-59.120
		(95.359)		(56.039)
Rcv. remittances (d)		-199.195^{**}		-78.182^{**}
		(17.089)		(12.016)
Tranche controls	Yes	Yes	Yes	Yes
N, 0-censored	1064	1064		
Total N	2868	2868	3021	3021
F	14.3^{**}	20.4^{**}	16.9^{**}	17.7^{**}
Pseudo-R^2 ($\hat{A}$ vs. A)	.18	.24	.15	.17

HHs with ≤ 4 children. Child reference category is 0 children. Sample weights used. Tobits display unconditional marginal effects at the mean (or 0 to 1 change for discrete variables, with all other [non-category] variables at the mean). Standard errors are heteroskedasticity-robust. $^{+}$, *, ** denote significance at 0.10, 0.05 and 0.01 levels. d indicates dummy variable.

TABLE 10: OLS REGRESSIONS: HOURLY EARNINGS, PRIME MEN AND WOMEN

	Pooled	Men	Women
Female	-2.401^{**}		
	(0.167)		
Age	0.958^{**}	1.070^{**}	0.804^{**}
	(0.063)	(0.088)	(0.090)
Age squared	-0.009^{**}	-0.010^{**}	-0.007^{**}
	(0.001)	(0.001)	(0.001)
Yrs. education	-0.839^{**}	-0.872^{**}	-0.799^{**}
	(0.081)	(0.131)	(0.090)
(Yrs. education)^2	0.116^{**}	0.119^{**}	0.111^{**}
	(0.008)	(0.012)	(0.009)
Urban	0.956^{**}	1.303^{**}	0.597^{**}
	(0.159)	(0.235)	(0.213)
Province controls	Yes	Yes	Yes
N	23212	12431	10781
F	79.5^{**}	47.6^{**}	41.7^{**}
Adj. R^2	0.11	0.10	0.11

Sample weights used. Standard errors are heteroskedasticity-robust. $^+$, *, ** denote significance at 0.10, 0.05 and 0.01 levels. d indicates dummy variable.

TABLE 11: ROTHBARTH REGRESSIONS OF COMPOSITE ADULT GOOD EXPENDITURE IN 2-ADULT HOUSEHOLDS: OLS AND TOBIT, ON QUADRATIC AND LINEAR (3.3) LOG FULL INCOME

	3.1 OLS	3.2 Tobit	3.3 Tobit
Urban (d)	-2.626	-4.901	-5.336
	(5.378)	(4.719)	(4.803)
Education (max. yrs.)	3.411^{**}	2.584^{*}	2.730^{*}
	(1.305)	(1.051)	(1.072)
Female HH head (d)	-43.661^{**}	-38.375^{**}	-38.148^{**}
	(5.846)	(4.773)	(4.816)
Oldest adult age	-0.416^{*}	-0.440^{**}	-0.441^{**}
	(0.182)	(0.163)	(0.164)
1 child (d)	-14.117^{+}	-14.083^{*}	-12.303^{+}
	(7.404)	(6.210)	(6.351)
2 children (d)	-29.146^{**}	-29.521^{**}	-28.261^{**}
	(7.888)	(6.439)	(6.400)
3 children (d)	-47.455^{**}	-45.584^{**}	-42.767^{**}
	(7.328)	(6.282)	(6.296)
4 children (d)	-38.463^{**}	-44.293^{**}	-43.501^{**}
	(11.111)	(9.648)	(9.613)
Ln(full income)	-129.336^{**}	-82.119^{**}	43.483^{**}
	(28.256)	(22.051)	(3.292)
(Ln(full income))^2	12.092^{**}	8.432^{**}	
	(2.024)	(1.566)	
Province controls	Yes	Yes	Yes
N, 0-censored		856	856
Total N	4888	4888	4888
F	39.5^{**}	36.1^{**}	35.9^{**}
Pseudo-R^2 ($\hat{A}$ vs. A)	0.205	0.214	0.208

2-adult HHs with $\leq$ 4 children. Child dummy reference category is zero children. Sample weights used. Tobits display unconditional marginal effects at the mean (or 0 to 1 change for discrete variables, with all other [non-category] variables at the mean). Std. errors are heteroskedasticity-robust. $^+$, *, ** denote significance at 0.10, 0.05 and 0.01 levels. d indicates dummy variable.

TABLE 12: ROTHBARTH REGRESSIONS OF COMPOSITE ADULT GOOD EXPENDITURE IN ALL HOUSEHOLDS: OLS AND TOBIT, ON QUADRATIC AND LINEAR (4.3) LOG FULL INCOME

	4.1 OLS	4.2 Tobit	4.3 Tobit
Urban (d)	13.227**	8.017**	8.009**
	(3.554)	(2.868)	(2.874)
Ln(HH size)	14.390*	11.228**	13.144**
	(5.616)	(4.347)	(4.371)
Education (max. yrs.)	1.950**	1.508**	1.536**
	(0.613)	(0.493)	(0.498)
Female HH head (d)	−27.521**	−25.898**	−25.633**
	(4.203)	(3.376)	(3.388)
Oldest adult age	−0.366**	−0.339**	−0.367**
	(0.121)	(0.100)	(0.101)
Majority men (d)	19.343**	14.124**	14.135**
	(4.950)	(3.854)	(3.868)
Majority women (d)	−13.540**	−13.218**	−12.883**
	(4.159)	(3.434)	(3.441)
1 child (d)	−27.926**	−26.581**	−26.392**
	(6.398)	(5.205)	(5.239)
2 children (d)	−49.367**	−46.274**	−46.801**
	(7.542)	(6.097)	(6.130)
3 children (d)	−53.641**	−49.760**	−50.644**
	(8.659)	(7.124)	(7.174)
4 children (d)	−51.862**	−50.146**	−52.187**
	(9.922)	(8.371)	(8.430)
Ln(full income)	−102.016**	−56.794**	43.790**
	(16.063)	(13.089)	(1.700)
$(\text{Ln(full income)})^2$	10.324**	6.722**	
	(1.143)	(0.919)	
Province controls	Yes	Yes	Yes
N, 0-censored		2926	2926
Total N	16049	16049	16049
F	87.5**	70.9**	71.4**
Pseudo-R^2 ($\hat{A}$ vs. A)	0.170	0.176	0.174

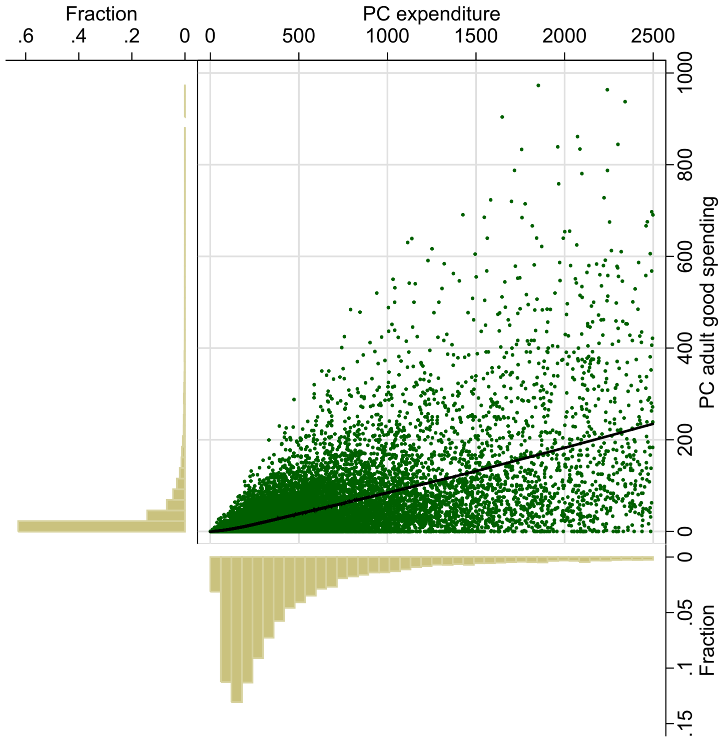
All HHs with ≤ 4 children. Child dummy reference category is zero children. Sample weights used. Tobits display unconditional marginal effects at the mean (or 0 to 1 change for discrete variables, with all other [non-category] variables at the mean). Std. errors are heteroskedasticity-robust. $^{+}$, *, ** denote significance at 0.10, 0.05 and 0.01 levels. d indicates dummy variable.

TABLE 13: FULL INCOME-BASED ROTHBARTH METHOD EQUIVALENCE SCALES

Children	One	Two	Three	Four	Mean
Scale against reference HH					
Restricted, linear	1.327	1.915	2.674	2.719	.
Restricted, quadratic	1.402	1.957	2.741	2.861	.
Unrestricted, linear	1.605	2.332	2.349	2.272	.
Unrestricted, quadratic	1.689	2.337	2.348	2.265	.
Mean adult equivalence					
Restricted, linear	0.654	0.915	1.116	0.860	0.886
Restricted, quadratic	0.803	0.957	1.161	0.930	0.963
Unrestricted, linear	1.211	1.332	0.899	0.636	1.019
Unrestricted, quadratic	1.377	1.337	0.899	0.633	1.061

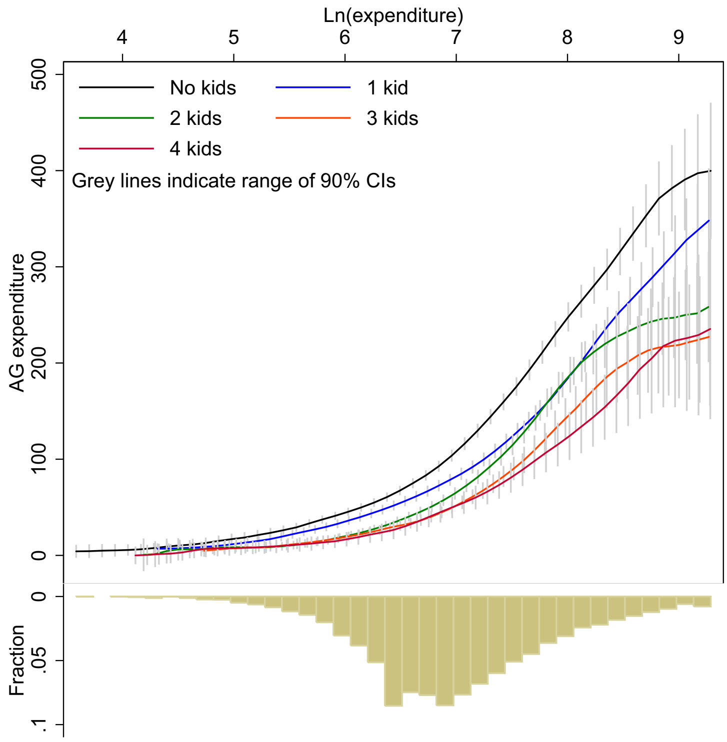
Scales are $\frac{Z_i}{Z_0}$, where Z_0 is full income in a 2-adult, 0-child reference household and Z_i is full income in a 2-adult, i-child household. Scales are full income-dependent in quadratic specifications; estimates at median full income per adult in HHs with given numbers of children reported.

FIG. 1: ADULT GOODS EXPENDITURE VERSUS TOTAL EXPENDITURE (PER CAPITA [PCE])



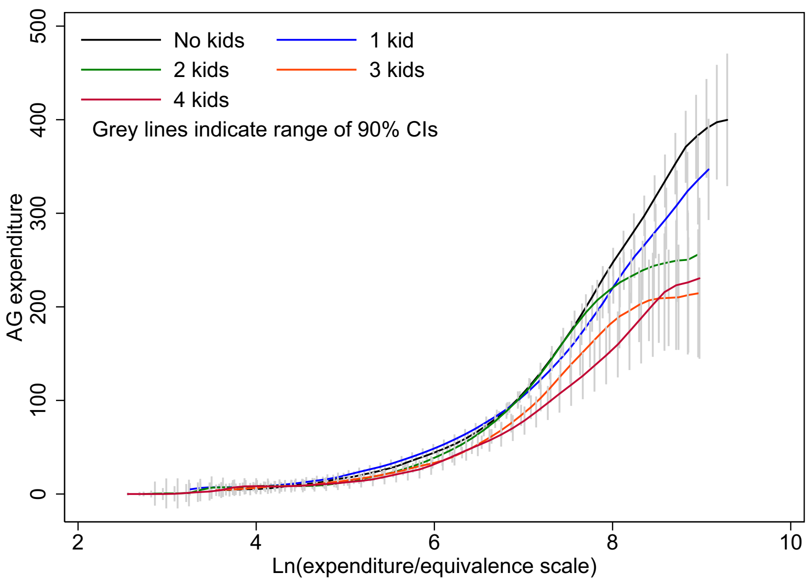
Scatter plot includes lowess regression curve (bandwidth: 0.5). For clarity, pce is truncated at the 96th percentile.

FIG. 2: LOCAL LINEAR REGRESSIONS OF ADULT GOOD EXPENDITURE ON LN(TOTAL EXPENDITURE): 2-ADULT HOUSEHOLDS, BY NO. OF CHILDREN



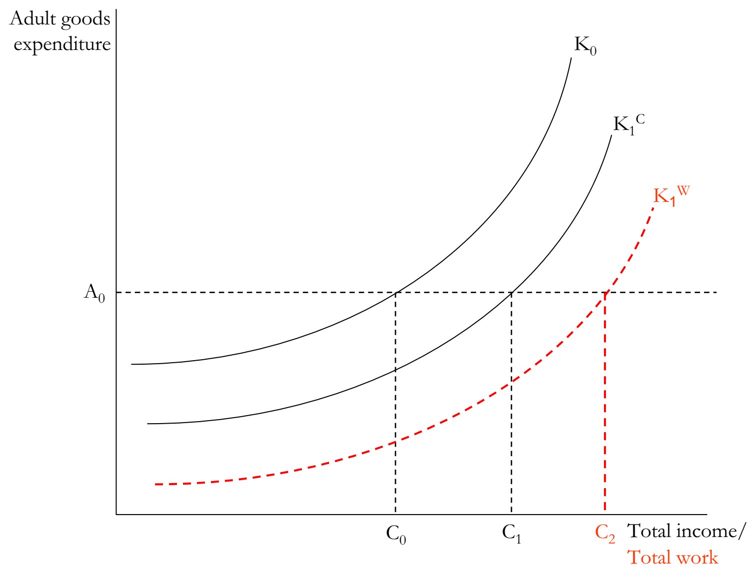
Bandwidth: 0.5

FIG. 3: LOCAL LINEAR REGRESSIONS OF ADULT GOOD EXPENDITURE ON COMPENSATED LN(EXPENDITURE): 2 ADULT HOUSEHOLDS, BY NO. OF CHILDREN



Bandwidth: 0.5. Compensation simulated by number of children and total expenditure, based on unrestricted, quadratic ln(x) Rothbarth specification.

FIG. 4: THE ROTHBARTH METHOD AND TIME COSTS



Adapted from Deaton (1997), page 256.

FIG. 5: PROPORTION OF PRIME ADULTS REPORTING ACTIVITY AT TIME OF DAY, BY GENDER (HHS WITH CHILDREN)

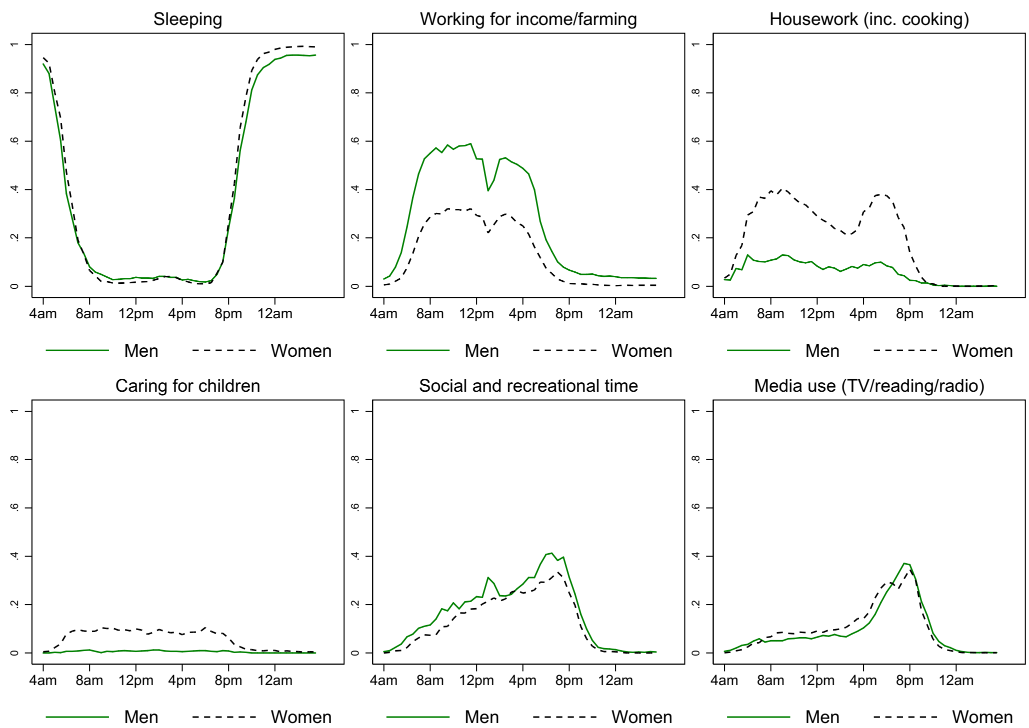


FIG. 6: PROPORTION OF 10-14 YEAR-OLDS REPORTING ACTIVITY AT TIME OF DAY, BY GENDER

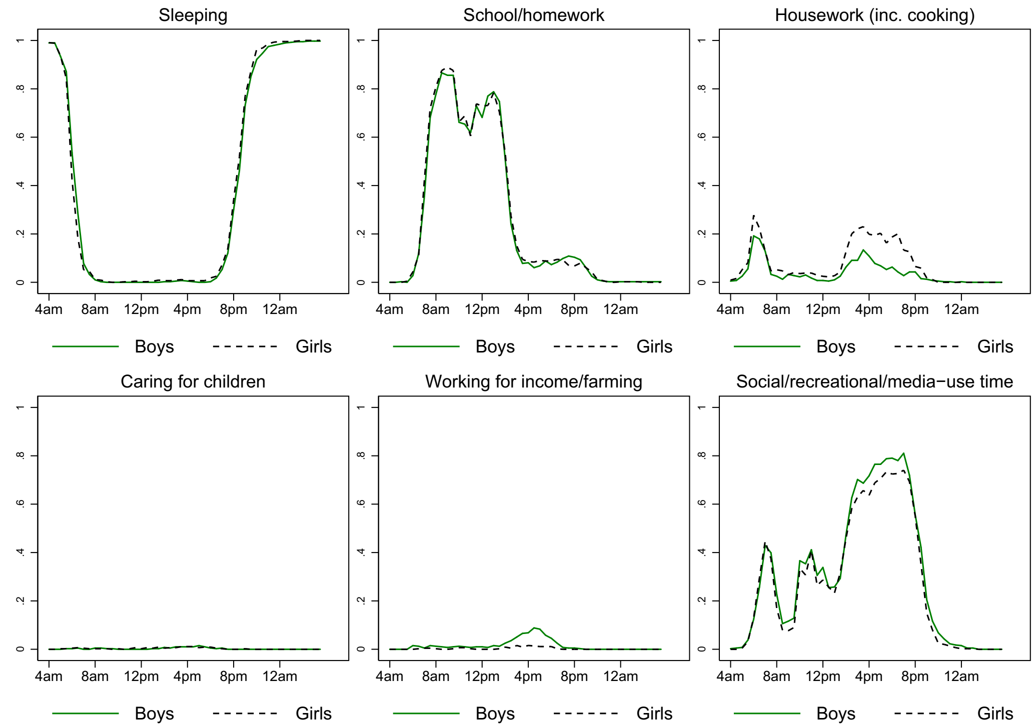
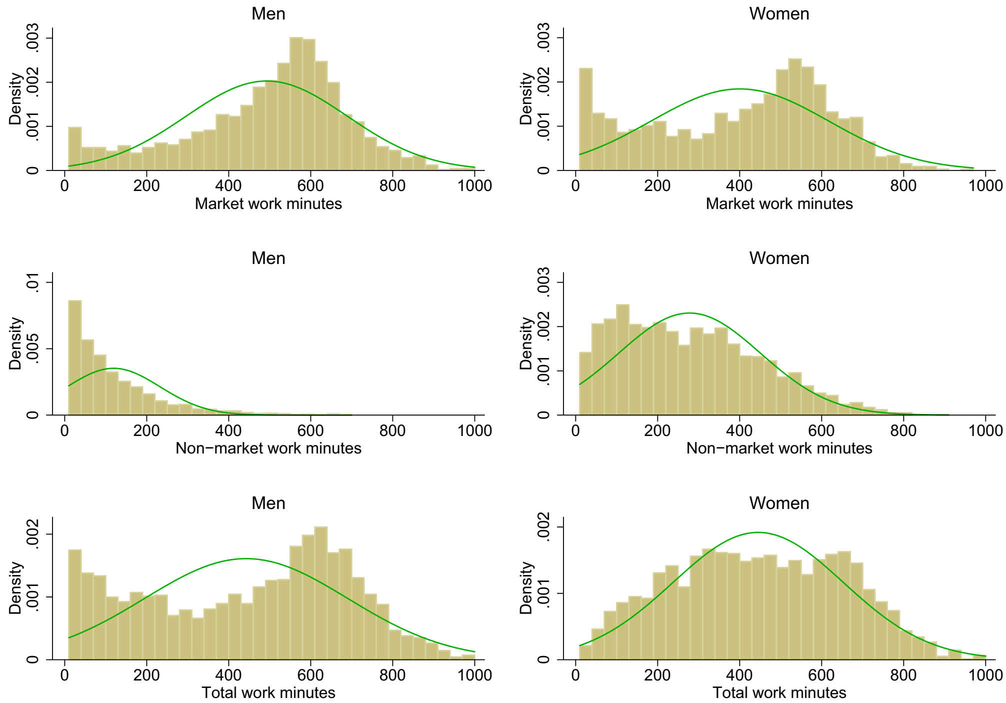
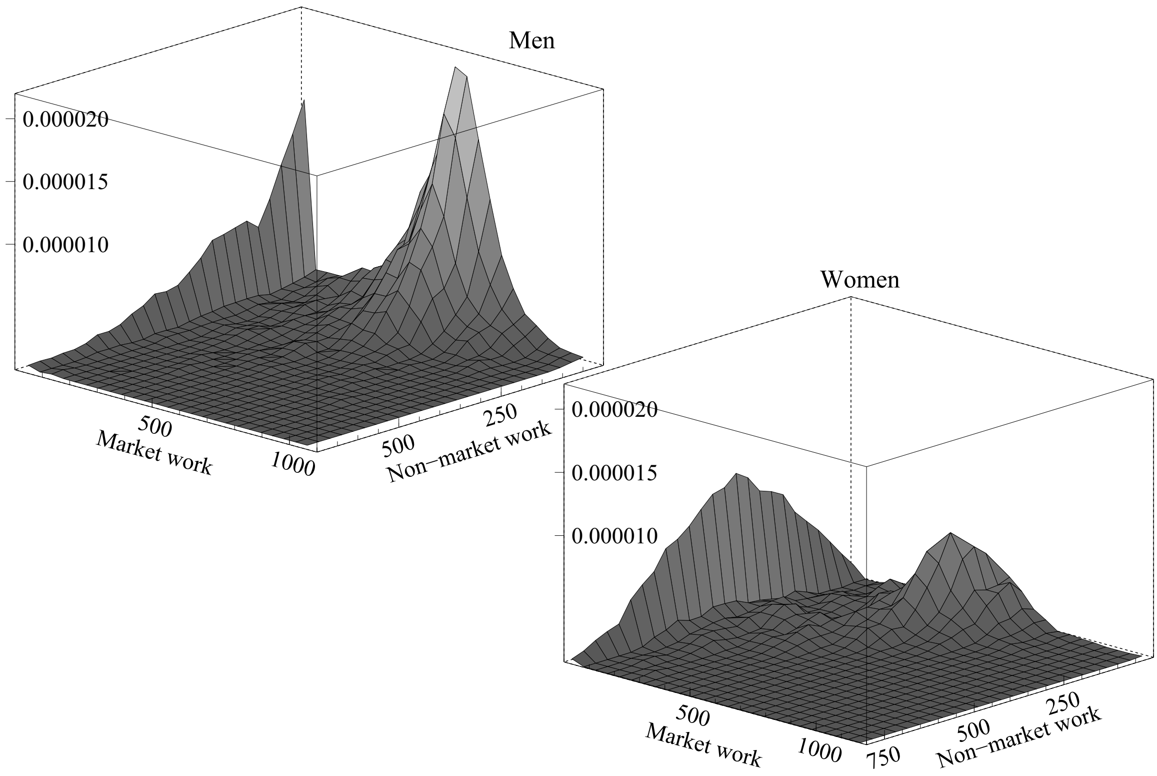


FIG. 7: WORK TIME HISTOGRAMS AND NORMAL CURVES: CONDITIONAL ON POSITIVE RELEVANT WORK TIME (PRIME ADULTS, TYPICAL DAY)



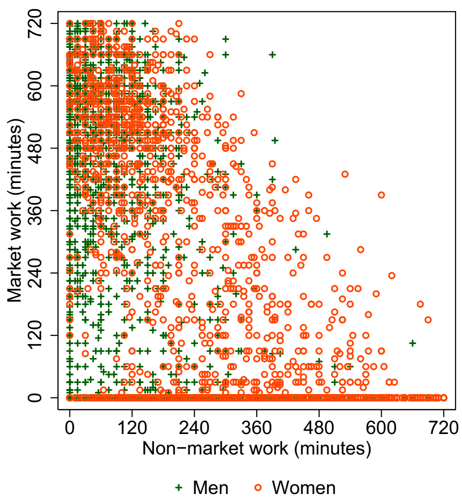
Bin width (universal): 30 minutes.

FIG. 8: MARKET AND NON-MARKET WORK TIME (MINUTES): ESTIMATED JOINT DENSITIES, BY GENDER



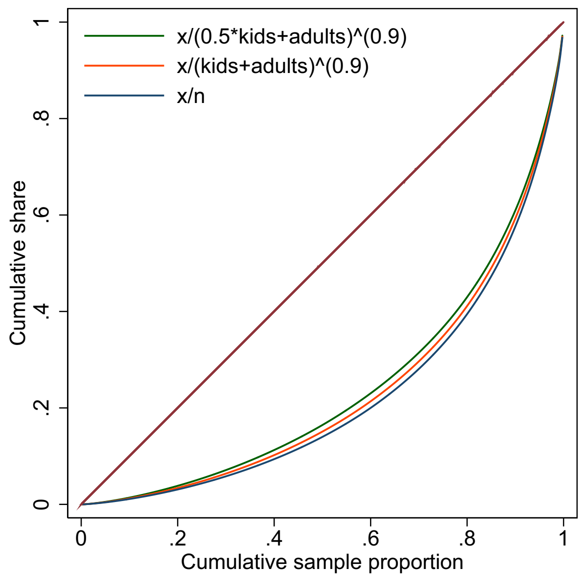
Working age adults on typical weekdays. Estimates based on Gaussian kernel with 20 minute half-width, evaluated at 75 axis points.

FIG. 9: MARKET AND NON-MARKET WORK TIME: SCATTER, BY GENDER



Working age adults on typical weekdays. Excludes 219 observations with > 720 minutes of market or non-market work time, for clarity.

FIG. 10: GENERALISED LORENZ CURVES, BY EQUIVALENCE SCALE



References

Ai, Chunrong and Edward Norton, "Interaction terms in logit and probit models," *Economics Letters*, 2003, *80*, 123–129.

Amoateng, Acheampong, Tim Heaton, and Ishmael Kalule-Sabiti, "Living Arrangements in South Africa," in Acheampong Amoateng and Tim Heaton, eds., *Families and Households in post-Apartheid South Africa: socio-demographic perspectives*, Human Sciences Research Council HSRC Press Cape Town 2007, pp. 43–59. Downloadable from www.hsrcpress.co.za.

Apps, Patricia and Ray Rees, "Household production, full consumption and the costs of children," *Labour Economics*, 2002, *8*.

Atkinson, A., N. Stern, and J. Gomulka, "On Labour Supply and Commodity Demands," in Angus Deaton, ed., *Essays in the Measurement and Theory of Consumer Behaviour*, Cambridge University Press 1981, pp. 265–296.

Banks, James, Richard Blundell, and Arthur Lewbel, "Quadratic Engel Curves and Consumer Demand," *The Review of Economics and Statistics*, November 1997, *79* (4), 527–539.

Barten, Anton, *Economic Analysis for National Economic Planning*, London: Butterworth, 1964.

Becker, Gary, "An Economic Analysis of Fertility," in "Demographic and Economic Change in Developed Countries" Universities-National Bureau Conference Series Princeton University Press Princeton 1960.

Bradbury, Bruce, "Using Time-Use Data to Estimate the Full Costs of Children," Paper presented at the 28th general conference of the International Association for Research in Income and Wealth May 2004.

Brathaug, Ann Lisbet and Debbie Budlender, "Calculating the Value of Unpaid Labour in South Africa," *Atlantis*, 2005, *28* (2).

Browning, Martin, "Children and Household Economic Behavior," *Journal of Economic Literature*, September 1992, *30* (3), 1434–1475.

Burton, Peter and Shelley Phipps, "Families, Time and Money in Canada, Germany, Sweden, the United Kingdom and the United States," *Review of Income and Wealth*, September 2007, *53* (3), 460–483.

Cichello, Paul, Gary Fields, and Murray Leibbrandt, "Earnings and Employment Dynamics for Africans in Post-apartheid South Africa: a Panel Study of KwaZulu-Natal," *Journal of African Economies*, 2005, *14*, 143–190.

Deaton, Angus, *The Analysis of Household Surveys – A Microeconomic Approach to Development Policy*, Baltimore: Johns Hopkins University Press, 1997.

——— **and Christina Paxson**, "Economies of Scale, Household Size and the Demand for Food," *Journal of Political Economy*, October 1998, *106* (5), 897–930.

____ **and John Muellbauer**, *Economics and Consumer Behaviour*, Cambridge University Press, 1980.

____ **and** ____ , "On Measuring Child Costs: with Applications to Poor Countries," *The Journal of Political Economy*, August 1986, *94* (4), 720–744.

Gronau, Reuben, "The Effect of Children on the Housewife's Value of Time," *Journal of Political Economy*, March 1973, *81* (2), 168–199.

____ , "The Allocation of Time of Israeli Women," *Journal of Political Economy*, 1976, *84* (4), 201–220. Part 2: Essays in Labor Economics in Honor of H. Gregg Lewis.

____ , "The Intrafamily Allocation of Goods-How to Separate the Adult from the Child," *Journal of Labor Economics*, July 1991, *9* (3), 207–235.

Guathier, Anne, Timothy Smeedeng, and Frank Furstenburg, "Are Parents Investing Less Time in Children? Trends in Selected Industrialized Countries," *Population and Development Review*, December 2004, *30* (4), 647–671.

Gustafsson, Bjorn and Urban Kjulin, "Time Use in Child Care and Housework and the Total Cost of Children," *Journal of Population Economics*, 1994, *7*, 287–306.

Haque, M., *Income Elasticity and Economic Development*, Vol. 42 of *Advanced Studies in Theoretical and Applied Econometrics*, Dordrecht, The Netherlands: Springer, 2005.

Johnson, Terry and John Pencavel, "Welfare Payments and Family Composition," in Philip Robins, ed., *A Guaranteed Annual Income: Evidence from a Social Experiment*, Academic Press New York 1980, pp. 223–240.

Keen, Michael, "Zero Expenditures and the Estimation of Engel Curves," *Journal of Applied Econometrics*, July 1986, *1* (3), 277–286.

Keswell, Malcolm and Laura Poswell, "Returns to Education in South Africa: a Retrospective Sensitivity Analysis of the Available Evidence," *South African Journal of Economics*, September 2004, *72* (4), 834–860.

Klasen, Stephan and Ingrid Woolard, "Determinants of Income Mobility and Household Poverty Dynamics in South Africa," *Journal of Development Studies*, 2005, *41* (5), 865–897.

Lanjouw, Peter and Martin Ravallion, "Poverty and Household Size," *The Economic Journal*, November 1995, *105* (433), 1415–1434.

Leibbrandt, Murray and Ingrid Woolard, "Measuring Poverty in South Africa," DPRU Working Paper 99.33, University of Cape Town October 1999.

____ **and** ____ , "The Labour Market and Household Income Inequality in South Africa: Existing Evidence and New Panel Data," *Journal of International Development*, 2001, *13*, 671–689.

____ and ____, "Towards a Poverty Line for South Africa: Background Note," South African National Treasury 2006. Available at http://www.treasury.gov.za/publications/other/povertyline.

Lewbel, Arthur, "Engel Curve," in Steven Durlauf and Lawrence Blume, eds., *The New Palgrave Dictionary of Economics*, Palgrave Macmillan 2008.

May, Julian, Michael Carter, and Dori Posel, "The composition and persistence of poverty in rural South Africa: an entitlements approach," Land and Agriculture Policy Centre Policy Paper No. 15 1995.

Nelson, Julie, "Household Equivalence Scales: Theory versus Policy?," *Journal of Labor Economics*, July 1993, *11* (3), 471–493.

Norton, Edward, Hua Wang, and Chunrong Ai, "Computing interaction effects and standard errors in logit and probit models," *The Stata Journal*, 2004, *4* (2), 154–167.

OECD, "What are Equivalence Scales?," Social and Welfare Statistics: Methods September 2005. available at http://www.oecd.org/dataoecd/61/52/35411111.pdf.

Papke, Leslie and Jeffrey Wooldridge, "Econometric Methods for Fractional Response Variables with an Application to 401(K) Plan Participation Rates," *Journal of Applied Econometrics*, 1996, *11*, 619–632.

Pollak, Robert, "Welfare Comparisons and Situation Comparisons," *Journal of Econometrics*, 1991, *50*.

Posel, Dori, "Counting the Poor: Who Gets What in Which Households?," *Agenda*, 1997, *Poverty Issue* (33), 49–60.

Prais, S. and H. Houthakker, *The Analysis of Family Budgets*, Cambridge University Press, 1955.

Punt, Cecilia, "Creating a 2000 IES-LFS Database in Stata," Provincial Decision-making Enabling Project (PROVIDE) Technical Paper 2005:1 February 2005. Available at www.elsenburg.com/provide.

Rama, Sharmla and Linda Richter, "Children's Household Work as a Contribution to the Well-being of the Family and the Household," in Acheampong Amoateng and Tim Heaton, eds., *Families and Households in post-Apartheid South Africa: socio-demographic perspectives*, Human Sciences Research Council HSRC Press Cape Town 2007, pp. 135–169. Downloadable from www.hsrcpress.co.za.

Robinson, Warren, "The Time Cost of Children and Other Household Production," *Population Studies*, July 1987, *41* (2), 313–323.

Rothbarth, Erwin, "Note on a method of determining equivalence income for families of different composition," appendix 4 of C. Madge, War time pattern of saving and spending, Occasional Paper 4, London, National Institute of Economic and Social Research 1943.

Statistics South Africa, "A Survey of Time Use: How South African Women and Men Spend Their Time," Technical Report, Statistics South Africa 2001.

Tansel, Aysit and Fatma Bircan, "Demand for education in Turkey: A tobit analysis of private tutoring expenditures," *Economics of Education Review*, 2006, *25*, 303–313.

Tsakloglou, Panos, "Estimation and Comparison of Two Simple Models of Equivalence Scales for the Cost of Children," *Economic Journal*, March 1991, *101* (405), 343–357.

Van der Berg, Servaas, "Fiscal Expenditure Incidence in South Africa, 1995 and 2000," Report for the National Treasury February 2005. Available at http://www.sarpn.org.za/documents/d0001113/index.php.

Van Hoa, Tran and D.S. Ironmonger, "Equivalence Scales: a Household Production Approach," *Economics Letters*, 1989, *31*, 407–410.

Wittenberg, Martin, "The School Day in South Africa," Working Paper 113, Centre for Social Science Research, University of Cape Town 2005.

Wooldridge, Jeffrey, *Econometric Analysis of Cross Section and Panel Data*, Cambridge MA.: MIT Press, 2002.

Yatchew, Adonis, *Semiparametric Regression for the Applied Econometrician* Themes in Modern Econometrics, Cambridge, UK: Cambridge University Press, 2003.

___ **, Yiguo Sun, and Catherine Deri**, "Efficient Estimation of Semiparametric Equivalence Scales with Evidence from South Africa," *Journal of Business and Economic Statistics*, 2003, *21* (2), 247–257.

Zellner, Arnold, "An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias," *Journal of the American Statistical Association*, 1962, *57*, 348–368.

A Child Age and Gender

A.1 Child Age

As noted in text, households with more children contain older children (see table 1). To the extent that older children have different consumption and time effects, the child age mix may be a systematic effect in the residual, correlated with child numbers and thus affecting reported results.

Existing, descriptive time use evidence suggests that non-market work is non-trivial, especially for girls (Wittenberg 2005); recall also figure 6. Diarists are at least 10, so child time allocations are available for 10-14 year-olds only (1,285 observations). Figure 11 (below) displays work time means by age and gender. Total work trends upwards in this age range. House work dominates, especially for girls (who work considerably more). Market work is negligible for girls; boys put in about half an hour of market work on average. Naturally, these means mask considerable variation: the standard deviation of total work is 110 minutes for boys and 120 for girls; 37% (30%) of boys (girls) record no work of any kind on their diary day.

Older children, then, clearly do contribute work (and extrapolating figure 11's evidence suggests that quite young children do so too). We are interested in the role this may play in adult work allocations, but evaluation is complicated both by the likely simultaneity of child and adult work determination, and the inability to observe both adult and child work in all but a few households. Similarly, child ages could affect the estimated consumption costs of children for given expenditure (in Rothbarth regressions).

The basic hypothesis is that younger and older children have different impacts, and (if older children assist with younger children, or if total child consumption varies by the age mix), that this impact varies by the number of children. The former is a one-dimensional child age effect, and the latter a child age/number of children interaction effect. Sample sizes in given child number categories in the IES and (especially) TUS are inadequate for convincing hypothesis testing using the child dummies which have captured child associations thus far. An alternative is to re-run regressions, using continuous child number and child age variables, and their interactions, instead of child dummies. To capture child age, the age of the oldest child in the household is used; this is the most relevant single measure of the child age distribution under the above hypothesis.

I re-run the unrestricted, quadratic expenditure Rothbarth regression (column 2.2 of table 3), and total male and female work regressions (columns 1.2 and 2.2 of table 9), in this form. The latter include potentially endogenous mean district unemployment and remittances received; as before, their exclusion has no impact on qualitative conclusions. Unlike in previously presented dummy variable regressions, there is no need to limit samples to households with four children or fewer. In the OLS case (female work), the marginal effects of interest are straightforward:

$$
\begin{aligned}
E(y|\mathbf{Z}) &= \beta_K(\text{kids})+\beta_A(\text{age})+\beta_{AK}(\text{kids}\times\text{age}) && (17)\\
\frac{\partial E(y|\mathbf{Z})}{\partial(\text{kids})} &= \beta_K+\beta_{AK}(\text{age}) && (18)\\
\frac{\partial E(y|\mathbf{Z})}{\partial(\text{age})} &= \beta_A+\beta_{AK}(\text{kids}) && (19)\\
\frac{\partial^2 E(y|\mathbf{Z})}{\partial(\text{kids})\partial(\text{age})} &= \beta_{AK}\ \textit{(pure interaction effect)} && (20)
\end{aligned}
$$

where $\mathbf{Z}$ is all non-child regressors. For Tobit regressions (adult spending and male work), adjustment for selection into observed positive values under Tobit model assumptions alters the equivalent expressions slightly. They are:

$$
\begin{aligned}
E(y) &= \mathbf{X}\beta\Phi\left(\frac{\mathbf{X}\beta}{\sigma}\right)+\sigma\phi\left(\frac{\mathbf{X}\beta}{\sigma}\right) && (21)\\
\frac{\partial E(y)}{\partial(\text{kids})} &= [\beta_K+\beta_{AK}(\text{age})]\,\Phi\left(\frac{\mathbf{X}\beta}{\sigma}\right)\text{, and} && (22)\\
\frac{\partial E(y)}{\partial(\text{age})} &= (\beta_A+\beta_{AK}(\text{kids}))\Phi\left(\frac{\mathbf{X}\beta}{\sigma}\right) && (23)\\
\frac{\partial^2 E(y)}{\partial(\text{kids})\partial(\text{age})} &= \beta_{AK}\Phi\left(\frac{\mathbf{X}\beta}{\sigma}\right)+[\beta_K+\beta_{AK}(\text{age})]\,\phi\left(\frac{\mathbf{X}\beta}{\sigma}\right)\left(\frac{\beta_A+\beta_{AK}(\text{kids})}{\sigma}\right) && (24)
\end{aligned}
$$

where $\mathbf{X}$ is all regressors, $\Phi(\cdot)$ and $\phi(\cdot)$ are the standard normal cumulative distribution and density functions, and σ^2 is variance. Note that expressions for adult goods consumption include $\ln(n)$ and its partial derivatives with respect to child number changes (not shown).[17] To save space, and since other coefficients and model diagnostics are generally unscathed, table 14 displays only relevant results, with marginal effects evaluated at sample means in the Tobit case.

The close link between the number of children and the child age mix makes collinearity a potential problem. The mean tolerance of child variables is under 0.2, compared to the ≤ 0.4 rule of thumb for multicollinearity with the potential to destabilise point estimates. Results may thus not be robust, but the pattern that emerges is certainly intriguing.

For adult goods, all marginal effects are significant, although only at the 10% level in the case of the interaction effect. Total child number and age associations are negative, and their interaction is positive. The interpretation is that both higher child numbers and ages tend to reduce adult spending, but that more of one weakens the effect of the other. It is helpful to plot the relationship between child numbers, maximum child age, and dependent variable predicted values as planes over the range of interest, and figure 12 does so for adult goods (for all child ages and up to six children).[18] Figure 12 illustrates the attenuating effect of the interaction clearly,

[17] Practically-minded readers should note that built-in marginal effects routines (such as Stata's "mfx" command) typically do not recognise interaction terms as comprising variables which also appear in levels. Consequently, the above expressions must be computed manually (Ai and Norton 2003, Norton, Wang and Ai 2004).

[18] Predicted values are calculated at the sample means of all non-child variables, and relevant values of child variables.

and shows that, in fact, as the number of children approaches six, the plane "twists" enough for the child number effect to essentially neutralise child age (age would do the same for child numbers too, if higher child numbers were displayed). The result is that in the presence of at least one older child, the marginal effect of more children is quite small. These results suggest that the consumption of older children is indeed more expensive. But older children also seem to reduce the effect of more children. If robust, this relationship drives down the marginal child costs obtained in reported Rothbarth regressions that do not control for child age.[19]

Turning to regressions of male and female work time (columns 2 and 3), only the marginal effect of child age is (weakly) significant in male work time. Given the insignificant interaction effect, and since we cannot be sure that child number point estimates are different from zero, it is most likely that, as before, children simply do not play a consistent role in determining total male work time.

Female work time associations, however, are again strong. The interaction term – the key variable – is significantly negative, while "kids" is significant and positive. The implication is that the positive effect of more children on female work time diminishes as the age of the oldest child increases. The total effect of age (by equation 19, not shown on table) is also significant. Figure 13 illustrates. All else equal, predicted work time is at its highest when there are many young children, and lowest when there are few, older children. Younger children, then, are the most directly time-intensive, and older children lessen marginal child time impacts (presumably by assisting adults).

These results suggest that child ages do play an important role, and so (given strong child/child age correlations) very likely affect cost estimates based purely on child numbers. As emphasised in the conclusion, this is irrelevant if the aim is to compensate parents with given numbers of children for their welfare loss. But it does matter if the aim is to measure the actual consumption needs of a child (in which case the first child might be the best measure). Unfortunately, these results are rather tentative. Collinearity may be affecting these point estimates, and if there are other sources of non-linearity in child costs by child number, then interaction term significance may also be an artefact of a misspecified linear, continuous child measure.

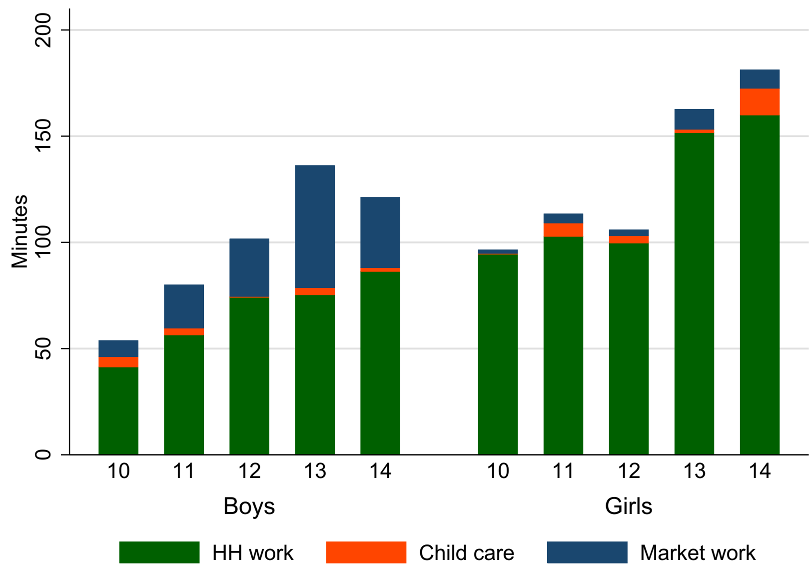
[19] While this relationship is rather mysterious, some possibilities include: (1) for a given number of children, consumption scale economies might be stronger for older children who are more "adult-like" in their consumption wants, and this may become material when there are many children, (2) older children might switch into consumption categories which confound the Rothbarth method (e.g. beginning to consume "adult" clothing).

TABLE 14: CHILDREN/CHILD AGE INTERACTIONS

Regression of:	1. Adult goods	2. Male work	3. Female work
	Marginal effect (rand)	Marginal effect (mins.)	Coefficient (mins.)
Kids	−5.652*	9.814	46.659**
	(2.697)	(10.084)	9.343
Age: max. child age	−1.755*	−4.151+	0.795
	(0.807)	(2.203)	1.460
Kids × age	0.398+	1.190	−2.793**
	(0.236)	(1.368)	0.783
Mean tolerance	0.142	0.152	0.189

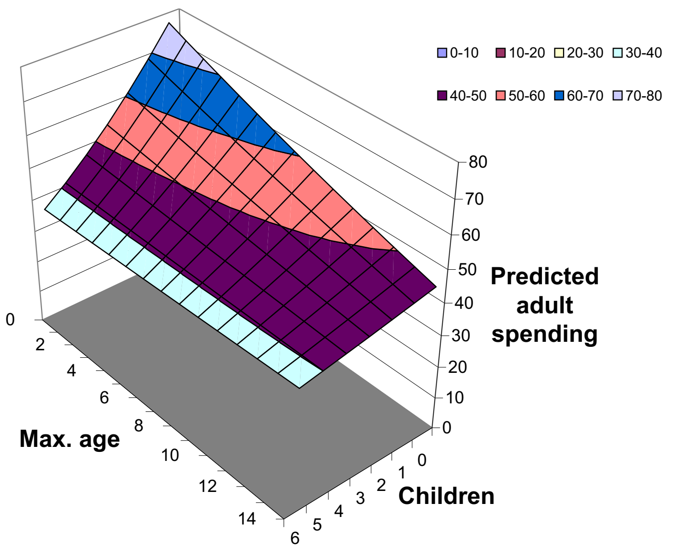
Reported variables substitute for child dummies in otherwise identical, previously reported regressions: (1) from column 2.2 of table 3, (2) and (3) from columns 1.2 and 2.2 of table 9. Marginal effects (columns 1 and 2) calculated at sample means. Tolerance reports mean of $1-R^2$ in OLS auxiliary regressions of displayed variables against all other regressors.

FIG. 11: CHILD WORK BY AGE AND GENDER: MEAN MINUTES PER DAY



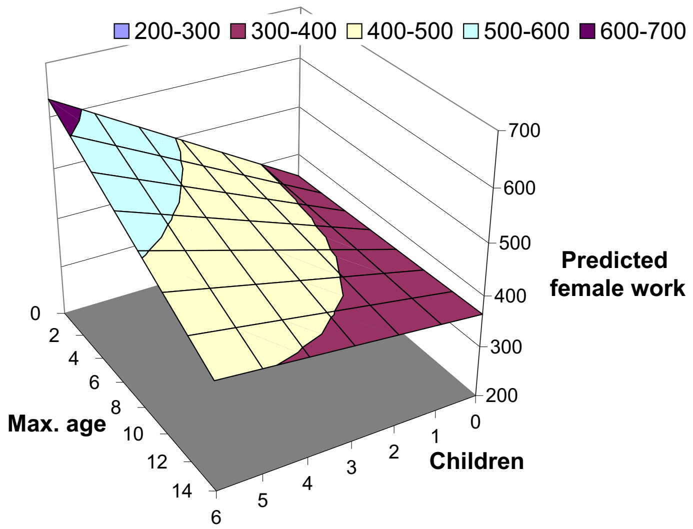
Typical days. Weighted sample.

FIG. 12: PREDICTED ADULT GOODS EXPENDITURE BY CHILDREN AND CHILD AGE



Source: Regression 1, table 14. Predicted values calculated at sample means of all non-child variables.

FIG. 13: PREDICTED FEMALE WORK TIME BY CHILDREN AND CHILD AGE



Source: Regression 3, table 14. Predicted values calculated at sample means of all non-child variables.

A.2 Child Genders

The above child number/age examination can be replicated for child genders, to evaluate whether child cost estimates suggest any differences. Continuous variables for the number of boys and girls, and an interaction term, are used. Table 15 reports results. Boys' and girls' marginal effects are indistinguishable in adult goods spending (column 1). The interaction effect is significant and positive, likely reflecting the child number effects discussed in section A. Child variables, as before, are insignificant in male work allocation. For female work, the estimated marginal effect of girls appears substantially lower than for boys, but the interaction term is insignificant. Re-running the regression without this term, we cannot reject the null hypothesis of equal boy and girl coefficients.

As suggested by the descriptive evidence (figure 11), it is possible that child work time differences by gender open a gender differential for older children only. Higher-order interactions could in principle be used to allow for age effects, but there is no obvious evidence that children of different genders have very different expenditure or time allocation impacts, except (perhaps) a hint that the marginal effect of girls on women's total work is a little lower than boys.

TABLE 15: CHILD GENDER COEFFICIENTS

Regression of:	**1. Adult goods**	**2. Male work**	**3. Female work**
	Marginal effect (rand)	Marginal effect (mins.)	Coefficient (mins.)
Boys	-6.751^{**}	6.379	20.524^{**}
	(1.916)	(7.838)	(6.078)
Girls	-6.235^{**}	.928	14.616^{**}
	(1.744)	(9.128)	(5.910)
Boys × girls	4.392^{**}	6.592	−2.368
	(1.086)	(7.383)	(4.070)
Mean tolerance	0.429	0.474	0.484

Reported coefficients are of variables substituting for child dummies in otherwise identical, previously reported regressions: (1) from column 2.2 of table 3, (2) and (3) from columns 1.2 and 2.2 of table 9. Tolerance reports mean of $1-R^2$ in OLS auxiliary regressions of displayed variables against all other regressors.

B A Robustness Check of Rothbarth Regressions

Engel curve estimation by Tobit has two major vulnerabilities, as described in section 2.3: heteroskedasticity, and the restrictive assumption of common effects on observation probability and the magnitude of spending. For the former, a natural log transformation is a straightforward way to reduce the dispersion of adult goods spending and thus risk of heteroskedasticity, but zero values are a problem since ln(0) is undefined.

One way of confronting these potential problems, and checking the robustness of Tobit estimates, is to assume that adult goods spending (A) is log-normally distributed and, following Wooldridge (2002), chapter 16, specify a hurdle model of the form:

$$P(A=0|\mathbf{X}) = 1-\Phi(\mathbf{X}\gamma) \tag{25}$$

$$\ln(A)|(\mathbf{X},A>0) \sim N(\mathbf{X}\beta,\sigma^2) \tag{26}$$

where $\mathbf{X}$ is all regressors, $\Phi(\cdot)$ is the standard normal cumulative distribution function, and σ^2 is variance. γ and β are conformable coefficient vectors on the regressor set, with variables now allowed to affect observation probability (equation 25) and conditional value (equation 26), differently. The resultant log-likelihood function yields:

$$E(A|\mathbf{X}) = \Phi(\mathbf{X}\gamma)\exp\left(\mathbf{X}\beta+\frac{\sigma^2}{2}\right) \tag{27}$$

$$\frac{\partial E(A|\mathbf{X})}{\partial x_i} = \left(\frac{\partial \mathbf{X}\gamma}{\partial x_i}\right)\phi(\mathbf{X}\gamma)\exp\left(\mathbf{X}\beta+\frac{\sigma^2}{2}\right)+\left(\frac{\partial \mathbf{X}\beta}{\partial x_i}\right)\Phi(\mathbf{X}\gamma)\exp\left(\mathbf{X}\beta+\frac{\sigma^2}{2}\right) \tag{28}$$

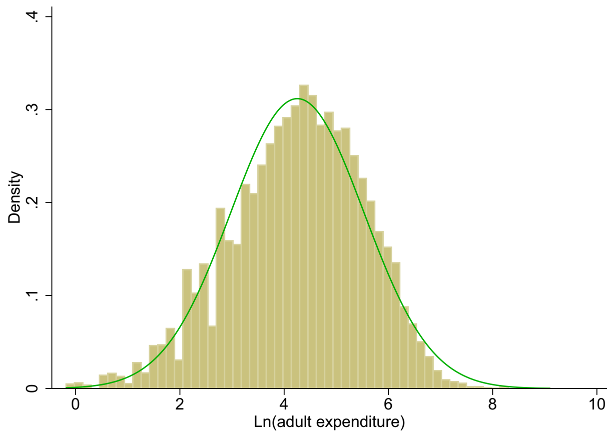
where $\phi(\cdot)$ is the standard normal density function, and equation 28 expresses the marginal effect of x_i (any continuous variable of interest in $\mathbf{X}$). Consistent estimates of the necessary parameters ($\hat{\gamma}$, $\hat{\beta}$, $\hat{\sigma^2}$) are obtainable from probit and OLS regressions of observation probability and the natural log of adult spending conditional on observation, respectively. See Wooldridge (2002) for details.

The advantage of this model is that it allows the assumption of common parameter effects to be relaxed, and involves a log-transformation of A that is likely to address the most obvious source of heteroskedasticity. The required log-normal error term for A seems likely to fit the data well (figure 14). However, given log-transformed adult good spending, the appropriate Engel curve specification needs to be reconsidered. On the basis of data inspection (figure 15), I assume that the log of adult goods spending is linear in the natural log of total expenditure (a "double log" Engel curve, which has desirable theoretical properties and is another common choice of functional form (Haque 2005)).

This model is applied (with other regressors unchanged) to the restricted (2 adult) sample, as described in section 2.3. Both classic, total expenditure-based Rothbarth estimates, and estimates based on the log of estimated, full income (as per section 4) are calculated. Rather than conduct formal model selection tests, I simply generate equivalence scale estimates which can be compared to those presented in tables 4 and 13. Note that, for both hurdle and previously reported Tobit models, estimated marginal effects for i children are based on dummy variable coefficients, and as such are calculated as the difference in $E(A)$ for the value of $\mathbf{X}\beta$ (and $\mathbf{X}\gamma$, for the hurdle model) at the mean of all regressors and i children (i.e. the coefficient on the i children dummy), and $E(A)$ for the value of $\mathbf{X}\beta$ (and $\mathbf{X}\gamma$) at the mean of all regressors and no children.

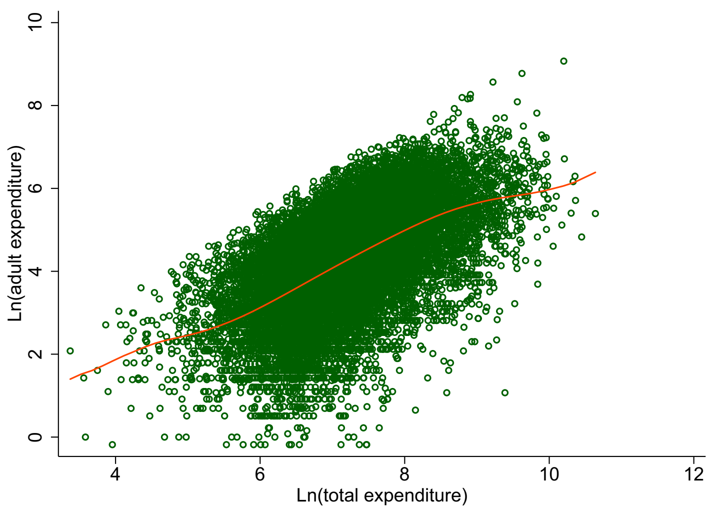
Table 16 summarises results. Estimated adult equivalences are similar to those calculated by Tobit in tables 4 and 13, with mean adult equivalences of about 0.5 and 1 under expenditure and full income constraints, respectively. Considering that the log dependent variable transformation ought to be less prone to heteroskedastic errors, and the greater flexibility of the hurdle model, this similarity with Tobit estimates is reassuring. This also suggests that mean equivalence scale estimates are not dominated by the choice of empirically-supported, and theoretically sensible, Engel curve functional form.

FIG. 14: HISTOGRAM AND NORMAL CURVE FOR NATURAL LOG OF ADULT GOODS EXPENDITURE



Conditioned on positive adult goods expenditure.

FIG. 15: LOG ADULT GOODS SPENDING AGAINST LOG TOTAL EXPENDITURE: SCATTER AND LOCAL LINEAR REGRESSION



Local linear regression bandwidth: 0.5. Conditioned on positive adult goods expenditure.

TABLE 16: HURDLE MODELS OF ADULT GOODS EXPENDITURE: CHILD MARGINAL EFFECTS AND ESTIMATED ADULT EQUIVALENCES

	Marginal effect (rand)	Equivalence Scale	Adult Equivalence
With total expenditure constraint:			
1 child	-9.631 ** (2.579)	1.256	0.513
2 children	-19.063 ** (2.645)	1.571	0.571
3 children	-23.625 ** (2.740)	1.750	0.500
4 children	-24.403 ** (3.406)	1.783	0.391
Average adult equivalence	0.494		
With full income constraint:			
1 child	-17.986 ** (5.842)	1.476	0.952
2 children	-32.830 ** (6.023)	2.035	1.035
3 children	-42.213 ** (6.291)	2.494	0.996
4 children	-54.564 ** (9.420)	3.258	1.129
Average adult equivalence	1.028		

Marginal effects estimated at zero values of other child categories, and sample means of other variables. Standard errors in parentheses. +, *, ** denote significance at 0.10, 0.05 and 0.01 levels.

C Data Decisions and Methodology

The following applies to all surveys:

- samples comprise only individuals who self-classify as black (about 80% of total).
- sample weights provided by Statistics South Africa are used in descriptive statistics (displayed means are estimated population means), and regressions (wherever model-compatible).

C.1 Income and Expenditure Survey

C.1.1 Data cleaning

Discrepancies between the 1995 and 2000 Income and Expenditure Surveys, and between the 2000 IES and national accounts data, have led to questions over the reliability of the IES (Van der Berg 2005). However, given that these data inform South Africa's consumer price indices, and the possibility that faults are also attributable to the surveys to which it is compared, use of the 2000 IES seems justified. However, data inspection and cleaning is likely to be even more important than usual. The following adjustments are made:

- 149 observations for which the difference between reported total income and expenditure is greater than two standard deviations are removed.
- 33 households reporting zero total expenditure, and a further 238 reporting zero food expenditure (including the estimated value of subsistence production), are removed.
- The total expenditure distribution is right-skewed, with a number of extreme outliers. Households in the top percentile of the expenditure distribution are removed (204 observations).
- The share of composite adult good spending in total expenditure reaches 84%, which seems suspiciously high. Based on examination of the distribution of adult goods spending, and the leverage plot of a simple regression of adult goods spending on the log of total expenditure (figure 16 below, which suggests that some extreme values are indeed mysterious in Engel curve estimates) the 6 households reporting adult goods expenditure shares of 65% and above are removed.

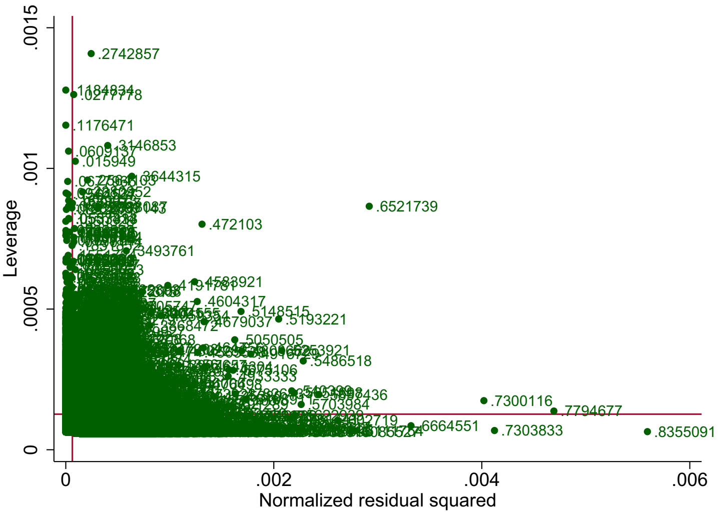
This leaves 20,128 valid observations, or 97% of the original (black-only) sample.

C.1.2 Composite Adult Good Construction

The composite adult good is the sum of:

- Alcoholic beverages consumed at home or elsewhere, over the month prior to the survey.
- "Cigarettes, cigars, tobacco and other items for smoking, and smokers requisites", over the month prior to the survey.
- Men's and women's clothing and footwear purchased over the last 12 months (including on credit). This is divided by 12 to yield a monthly average. This overcomes the infrequent purchases problem that would pollute measures based on the previous month's expenditure on lumpy goods like apparel.

FIG. 16: LEVERAGE PLOT: REGRESSION OF ADULT GOODS SHARE ON LOG TOTAL EXPENDITURE



Marker labels indicate adult goods share.

C.2 Time Use Survey

The TUS is a unique, nationally-representative time use survey of South African households. Survey methodology was informed by international best practise for capturing time use information. Two members in each surveyed household ("diarists") were asked to supply information on their activities on the previous day. The format of the resultant time diaries – capturing up to 144 activities in the 24-hour day – is described below. In addition to the diaries, basic household characteristic, and demographic composition, variables are captured, along with more detailed information on diarists.

After cleaning, the final sample comprises 9,073 diarists in 5,413 unique households.

C.2.1 Activity definitions

Activities are defined as follows (descriptions extracted from TUS code sheets):

- Work – the sum of:
  - Market work: any activities in the "employment for establishments" and "services for income and other production of goods not for establishments" categories (including travel and job search time); primary production activities generating income substitutes, for own-consumption or sale: crop farming and market/kitchen gardening (planting, weeding, harvesting, picking, etc.); tending animals and fish farming; hunting, fishing, gathering of wild products and forestry; purchase of goods for and sale of outputs arising from these activities.
  - Non-market work – the sum of:
    * House work: any activities in the "household maintenance, management and shopping for own household" category (primarily cooking, cleaning, shopping

and household management [planning, supervising, paying bills etc.]); primary production activities to satisfy household service needs: collecting fuel, firewood or dung, digging, stone cutting, splitting and carving, collecting water.

* Child care: physical care (washing, dressing, feeding); teaching, training and instruction of household's children; accompanying children to places: school, sports, lessons, etc.; supervising children and adults needing care; travel related to care of children, the sick, elderly and disabled in the household; care of children, the sick, elderly and disabled in the household not elsewhere classified.

- Leisure: any kind of media use (primarily TV and radio); any activity in the "social and cultural activities" category (primarily socialising with family and non-family); eating and drinking; doing nothing/rest/relaxation; individual religious practises/meditation.

- Other: community services (full category; e.g. uncompensated help to other households, community meetings); learning (full category [primarily school attendance, homework, studies and course review, learning-related travel]); personal hygiene; medical and related personal care.

The key classification decisions concern the assignment of primary production activity to market and non-market labour time. I assume that fuel and water collection are mainly household services, rather than for sale or earnings substitution. Key results are not sensitive to redefinitions favouring market labour. Time spent "supervising children and adults needing care", and related travel, time is assigned to child care, though some of it may apply to adults. By far the bulk of care time, however, is attributed unambiguously to child care, and the exclusion of the above ambiguous categories from child care time has no material impact on results.

It is notable that the TUS tries to minimise the known tendency of time use surveys to underestimate care time; surveyors prompt diarists to recall any additional child care time not mentioned spontaneously in their diaries. Child care time includes all such additional values.

C.2.2 Time Measurement

The TUS allows diarists to record up to 3 activities per half hour time slot, and records whether activities are performed simultaneously or sequentially. Researchers then have the option of apportioning time for simultaneous activities so that total time adds up to 1440 minutes a day, or counting total time spent in an activity in full – even if other activities are occurring simultaneously (so-called "full time"). In the latter case, total time use may add up to more than a day. It is not obvious how to handle simultaneous activities sensibly (how much "leisure" occurs if a respondent works an eight hour day while simultaneously listening to the radio, for example?), and the issue is not trivial if activities of direct interest – notably child care – frequently overlap with others. Indeed, 36% of child care mentions coincide with other activities (primarily leisure [the other activity in 55% of simultaneous childwork mentions], and house work [31%]).

I experimented with the standard time allocation method (dividing total time amongst simultaneously performed activities, so that two (three) simultaneous activities over a half hour period were assigned fifteen (ten) minutes each), full time, and a modified variant of full time where if simultaneous activities were all work these were divided up equally, while simultaneous child work and leisure were counted as leisure. Predictably, the standard full time method yielded somewhat higher child cost estimates. The basic and modified full time methods generated almost identical estimates. On these grounds, the basic method was used (time is divided equally amongst simultaneous activities, and activities must add up to a day); this measure is also more transparent, and yields marginal effects which are easier to interpret.

Measurement error is a natural worry in time use data, and is of particular concern if errors are non-random (e.g. more likely for poorer, rural respondents whose lifestyles do not involve much clock-watching). 46% of the final sample – and 53% of the prime adults who are the focus – answered yes to the question "do you usually wear a watch or have a clock with you?". For prime age respondents, the rural-urban difference is quite modest – 47% of rural respondents against 57% of urban. Examination of the data suggests very few obvious anomalies (activity by time of day figures are particularly useful in this respect), and I proceed on the assumption that any measurement errors are ignorable. One surprise, however, is the amount of time spent sleeping – 584 minutes, or 9.7 hours on average, which appears high. Essentially the same numbers are reported (without comment) in Statistics South Africa's survey findings summary (Statistics South Africa 2001). There is substantial variation (including by age, employment status [an hour less sleep for the employed] and electrical power in the household [45 minutes less]).

C.2.3 Days of the Week and Atypical Days

11% of prime adult diaries are recorded on a Saturday, and 17% on a Sunday. Diarists are asked whether their diary day was "typical". If not, there is limited information on why (reasons include weather, work leave, family problems, and a large "other" category). 16% of all observations are described as atypical, but only 8% of weekend days are described as atypical "because it was a weekend day". As we would expect, market work means are substantially lower on Saturdays and – especially – Sundays (and roughly constant across week days). Consequently, it seems probable that many weekend respondents interpreted the question as asking how typical their recorded day was, *for* a weekend!

There is no strong evidence that the day of the week reported, or typicality, are correlated with observable characteristics, so it is unlikely that excluding atypical and weekend days would cause selection bias. But this would mean the loss of 38% of prime diarist observations, which is excessive unless there are very strong grounds for thinking that such observations really are unrepresentative of people's experiences. I err on the side of maintaining the full sample, using dummy variables for Saturday, Sunday and self-declared atypical days. Descriptive statistics exclude atypical day observations (but include typical weekend days); the patterns displayed are fairly robust to these choices.

C.3 Labour Force Survey

C.4 Data Decisions

C.4.1 Subsistence Production

Earnings from the LFS include all market labour income, but exclude the value of food grown for own consumption. It is possible to recover the net value of subsistence production (at the household level) from the IES, and match it to individuals who report growing food for non-recreational reasons. Doing so generates earnings for 4,605 people with zero market earnings.

However, subsistence farming is much more likely to be a supplement to other income sources than a freely chosen alternative to market employment (Cichello, Fields and Leibbrandt 2005), so the inclusion of this earnings type in conventional market earnings models is questionable in principle, while also creating a problematic tail in the earnings distribution, comprising these very low "earners". Consequently, the earnings utilised consist of market labour earnings only.

C.4.2 Missing Earnings

Respondents who do not know, or refuse to provide, labour earnings are prompted to select 1 of 14 weekly, monthly or annual earnings categories. In these cases (7.6% of total non-zero earnings observations used), earnings are assumed to be at category midpoints, and twice the top (open-ended) threshold, which begins at 30,001 rand a month. The addition of category variables makes the earnings data more coarse, but since the evidence is that individuals reporting earnings in categories tend to be higher earners (their hourly earnings are 11% higher than other positive earners when their earnings are assumed to be at category minima, and 38% higher at the midpoints), omitting them would risk a serious missing values problem. Earnings data remain missing for 3,030 individuals who appear to be employed (14.5% of the employed).

C.4.3 Missing Hours

323 earners (2% of sample used) with missing hours data are assigned 45 hour work weeks.